International Review of Accounting, Banking and Finance
Vol 6, No. 3 / 4, Fall / Winter 2014 Pages 1~32
IRABF

The Impact of Customer Satisfaction on Analysts' Earnings Forecast

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ABSTRACT

This study investigates whether the accuracy of analyst forecasts is affected by customer satisfaction. Using a sample of 1,005 U.S firm year observations, we find that properties of forecast quality, namely consensus accuracy, forecast dispersion, forecast range, is positively associated with customer satisfaction. We further find that analysts' cash flow forecast properties are also affected by customer satisfaction in a similar way. Overall, our study suggests that information intermediaries, such as financial analysts, do take into account customer satisfaction in their forecasting activities. As analysts' forecast accuracy affects investment risk, we contribute to the literature by providing evidence that customer satisfaction is value relevant to investors. We corroborate our conclusion by showing that the negative association between analysts' earnings forecasts and cost of debt is stronger for firms with higher customer satisfaction.

Keywords: Customer satisfaction, analysts' earnings forecast, analysts' cash flow forecast, forecast accuracy, forecast dispersion, forecast range
JEL: E20, E27, G14, G19, G39, M39

1. Introduction

Apart from financial statements prepared by management, various public and private information collected and interpreted by financial analysts are perhaps the single most important alternative source of financial information. Evidence suggests that financial analysts and their work are likely to influence both investors and standard setters (for example, Hou, Hung and Gao, 2014; Call, Chen and Tong, 2009; Wild, Bernstein and Subramanyam, 2001). A survey by the Financial Executives Research Foundation suggests that analyst reports are a major source of information to individual investors (SRI International, 1987). Forecasting earnings and recommending stocks are two of the most vital services performed by financial analysts. The earnings forecasting literature documents that firms meeting analysts' earnings forecasts experience positive stock price changes and favorable valuation consequences (Bartov, Givoly, and Hayn, 2002; Lopez and Rees 2002), while those missing earnings forecasts suffer adverse valuation consequences (Skinner and Sloan, 2002). Analysts' earnings forecasts also affect resource allocation (e.g. Xidonas and Doukas, 2013; Larocque, 2013). If analysts are too optimistic or pessimistic about some firms, there is chance of allocating too much (little) weight to over-(under-) valued stocks. Such misallocation may result in abnormal stock price movement and in turn economic loss both for investors and the economy as a whole.

Existing literature has identified various factors that will make a difference on analysts' forecast accuracy. Individual differences among analysts including their own ability, resources, portfolio complexity, behavioral preference (Clement 1999; Kini, Mian, Rebello and Venkateswaran, 2009; Salamouris and Yaz, 2010; Hsu and Chiao, 2011; Luo and Xie, 2012 Liang and Riedl, 2014; Abdallah, Abdallah and Ismail, 2012) are well documented as contributors to analyst forecast quality. Besides, firms' own characteristics such as management's incentives (Kanagaretnam, Lobo and Mathieu, 2012), and international diversification (Duru and Reeb, 2002), industry features (Kwon, 2002) are found to have a significant impact. Moreover, external factors such as macroeconomic elements regulations, accounting standards, corporate governance (Hope, 2003; Mensah, Song and Ho, 2004; Bhat, Ole-Kristian and Kang, 2006; Anagnostopoulou, 2010; Chen, Ding and Kim, 2010; Dhaliwal, Radhakrishnan, Tsang and Yang, 2012; Black and Carnes, 2006; Gul, Hutchison, Lai, 2013; Salerno, 2014; Liu, Wang and Yao, 2014) are also extensively investigated and found to be impactful on analyst forecast properties.

Extant evidence shows that analysts use financial and non-financial information to provide forecasts. However, previous research has not touched much upon whether a firm's management practices, particularly marketing strategies, play a role in analysts' forecasts. In this paper, we investigate how marketing strategies, proxied by customer satisfaction, affect analyst forecast properties. We focus on customer satisfaction for two reasons. *First*, customer satisfaction has recently attracted a considerable amount of research and practitioner interests in the marketing literature. Research evidence suggests that higher levels of customer satisfaction affect customer behavior in many positive ways. Favorable customer behavior includes higher repurchase (Mittal and Kamakura, 2001), increased usage level (Bolton, 1998), less complaints (Fornell, 1992), lower future transaction costs (Reichheld and Sasser, 1990), lower warranty and field service costs (Fornell and Lehmann, 1994), and higher price increase tolerance (Fornell et al. 1996). These positive customer behaviour outcomes are likely to translate into higher revenue and lower costs, and thus higher profitability and operating cash inflows. It is therefore not surprising that firms increasingly spend more on strategies designed to increase customer satisfaction. *Second*, existing evidence on the relationship between customer satisfaction and stock market behaviour is mixed. For example, Anderson, Fornell and Mazvancheryl (2004) report a positive relation between customer satisfaction and Tobin's Q, their proxy for shareholder value. Similarly, Fornell, Mithas, Morgeson and Krishnan (2006) suggest that investment in high customer satisfaction firms have higher market returns and lower systematic risk. Recently, Anderson and Mansi (2009) show that customer satisfaction is associated with lower bond yield rates and higher credit ratings in the financial market. Other studies, however, suggest that customer satisfaction does not have a significant impact on financial markets. Both Ittner and Larcker (1998) and Fornell et al. (2006) find that the announcement of customer satisfaction measures has no effect on stock prices and that the association between customer satisfaction and accounting performance is positive but insignificant. Fornell et al. (2006) also find that a customer satisfaction announcement has no association with stock price movements. Jacobson and Mizik (2009) suggest that prior research which has documented an abnormal positive return by investing in high customer satisfaction firms is based on a small set of firms in the computer and internet industry and cannot be generalized to other industries. Finally, Ittner, Larker and Taylor (2009) apply a more comprehensive set of well-established tests from the accounting and finance literature to show that ACSI does not predict long-term returns. Most of these studies focus on stock market behaviour and apart from Andersen and Mansi (2009), little is known about whether customer satisfaction affects other market participants such as finance providers and financial analysts. Therefore, an investigation of how key market participants view customer satisfaction is vital for advancing our understanding of the role of customer satisfaction in financial markets.

In this study we examine whether customer satisfaction is associated with the accuracy analysts' earnings forecast and cash flow forecast. We also include cash flow forecasts accuracy in our analysis since prior research shows that (1) analysts' earnings forecasts issued together with cash flow forecasts are more accurate than those not accompanied by cash flow forecasts and (2) analysts who issue both earnings and cash flow forecasts adopt a more structured approach in their work (Call, Chen and Tong, 2008). Besides, the accuracy of cash flow forecasts issued by financial analysts is similar to that of earnings forecasts (Pae and Yoon, 2012). Therefore, we investigate the impact of customer satisfaction on both earnings and cash flow forecasts.

In summary, given the importance of financial analysts as information intermediaries who receive and process information for investors and their role in financial markets, it is important to understand whether analysts are affected by various marketing strategies including attempts by management to improve customer satisfaction.

Using U.S data for the period 1995-2007 and 1,005 firm year observations, we show that a higher level of customer satisfaction is associated with more accurate analysts' earnings and cash flow forecasts. These results should be of interest to both financial and marketing academics and practitioners for the following reasons. *First*, given that better analysts' forecasts may affect participants in the financial market, this finding has implications for marketing strategies since it suggests that expenditure on improving customer satisfaction may have indirect benefits in terms of greater investor interests. Thus, marketing activities designed to improve customer satisfaction could affect the cost of capital indirectly through financial analysts' predictions. *Second*, marketing directors are under growing pressure to demonstrate benefits of marketing expenditures (Rust et al. 2004) and the positive link between customer satisfaction and analysts' forecast properties may be used as evidence to justify their marketing expenditures to maintain and raise customer satisfaction. *Finally*, our finding has implications for investors as analyst forecast is important in their investment decision. Large forecast error may mislead them in making inappropriate decisions and a loss in their personal wealth. With the findings in this study, investors refer to a relatively simpler and less expensive index, customer satisfaction, as a proxy for the accuracy of the expected future earnings and cash flows.

2. Literature Review and Hypotheses Development

2.1 Related Prior Studies on Analysts' Earnings Forecast Accuracy

Financial analysts are primarily information intermediaries who collect and process firm information, and transfer the processed information to users in financial markets. A typical analysis of a stock normally starts with an exhaustive review of the firm's history, its products and markets, and its earnings, dividends, and financial status both currently and on a projected basis. The end product of the analysis is a projection of earnings over a given time period.

Analysts study firms to arrive at an estimate of their financial values. A normal practice is to conduct financial forecasts to estimate the future financial outcomes of firms – earnings forecast. This can be done using historical financial statements, as well as external market and economic projections. Analysts thus need to collect and interpret economic, strategic, financial and non-financial data relating to a firm so as to assess the future earnings and the firms' value for their customers' investment decision making.

Prior studies have documented various factors that affect analysts' earnings forecast properties. As discussed previously, both analysts' preferences and external factors have impact on the forecast accuracy. Besides, firm characteristics also make a difference. Lang and Lundholm (1996), for example, use analysts' evaluation of firms' disclosure to show that a high disclosure level has a larger number of analysts following it, less analyst earnings forecast errors and less dispersion among analyst forecasts and also less volatility in forecast revisions. Their results suggest that lower information asymmetry is associated with better analysts' forecast accuracy and less dispersion. Kross, Ro and Schroder (1990) indicate that earnings volatility is associated with lower forecast accuracy. Eames and Glover (2003) document a position association between earnings level and analyst forecast error. Hwang, Jan and Basu (1996) suggest that loss firms have more forecast errors. However, no prior study has examined the association between customer satisfaction and analyst forecast properties.

2.2 Prior Studies on Customer Satisfaction

Prior work has documented evidence that customer satisfaction affects customer choice and behaviour. A higher level of customer satisfaction leads to higher customer loyalty (e.g. Anderson and Sullivan, 1993). High customer satisfaction and loyalty is effective in retaining customers at a low cost. To acquire a new customer entails certain one-time costs of advertising, promotions, and the like. New customers may not spend large amounts on the firms' products/services in the beginning on a trial basis, whereas no special spending is required to retain a customer with absolute loyalty with no extra cost at all. Besides, high customer satisfaction is associated with positive customer behavior including lower future transaction costs (Reichheld and Sasser, 1990), less complaints and thus lower complaint handling costs (Fornell, 1992), lower field service and warranty costs (Fornell and Wernerfelt, 1987), increased usage (Bolton, Kannan and Bramlett, 2000), higher repurchase intention (Mittal and Kamakura 2001), lower negative impact of price increases (Homburg, Hoyer and Koschate 2005), decreases price elasticity (Anderson, 1996), so customers are willing to pay more (Homburg, Koschate, and Hoyer 2005), and greater customer commitment to the firm (Gustafsson, Johnson, and Roos, 2005).

2.3 Hypotheses Development

Marketing strategy contributes to a firm's primary objective of profit maximization. A direct result of marketing strategy, customer satisfaction and its impact on consumer behavior has been well documented. For example, customer satisfaction can help to retain customers due to higher perceived quality (Anderson and Sullivan, 1993) and repeated purchases (LaBarbera and Mazursky, 1983; Mittal and Kamakura, 2001). The greater commitments from satisfied customers lower the intention of customers to switch to another brand (firm) and thus lower the sensitivity of a firm's cash flow, especially during an economic downturn. Positive word-of-mouth, in general, has more credibility than advertising which leads to (1) increased revenue through new customers acquisition (Fornell, 1992; Mooradian and Olver, 1997) and cross-buying of the firm's products due to positive associations about the parent brand (Li, Sun, and Wilcox, 2005) and (2) decreased marketing-related expenses due to the 'free' advertising (Luo and Homburg, 2007). Besides, the high satisfaction results in a stable customer base which in turn gives more time for a firm to better understand these customers, including their tastes and demand patterns (Tuli, Kohli, and Bharadwaj, 2007). Such a customer base puts firms at an advantage in anticipating changes in customer demand, inventory control and product development. Therefore, higher customer satisfaction brings economic benefits to firms by providing greater revenue stability, more predictable cash inflows and more controllable costs. Consequently, the uncertainty in the forecasting process would be greatly reduced.

In sum, customer satisfaction helps to generate stable and sustainable revenue from both existing and new customers, as well as lowering the various costs in operation. We therefore posit that higher customer satisfaction is able to enhance the predictability of future earnings and lower the uncertainty in an analyst's forecasting process.

Finance literature usually uses three properties to measure forecast accuracy, namely forecast error, dispersion and range. While forecast error is simply the difference between consensus earnings forecast and the actual earnings, analysts' forecast dispersion is commonly viewed as a measure of ex ante earnings uncertainty (Imhoff and Lobo, 1992). Hermann and Thomas (2005) consider larger dispersion as suggesting less agreement among analysts regarding expected earnings due to the inability or unwillingness of some analysts to fully and objectively gather and process information. Hence, analysts with more precise information regarding future earnings should agree more and have a smaller dispersion. Customer satisfaction makes the prediction of future revenue and earnings easier and more accurate, and should thus result in lower forecast dispersion. Similar to dispersion, forecast range, being the difference between the maximum forecast and the minimum forecast by individual analysts, also measures the uncertainty about future earnings among analysts. Given the previous discussion on the positive impact of customer satisfaction, we therefore have the following hypotheses:

H1: Customer satisfaction is negatively associated with analysts' earnings forecasts error

H2: Customer satisfaction is negatively associated with analysts' earnings forecasts dispersion

H3: Customer satisfaction is negatively associated with analysts' earnings forecasts range

3. Research Methodology

3.1 Measuring Analysts Forecast Properties

Earnings Forecast Error

$$ACCY_t = (\mid FORECAST_t - EPS_t \mid \div PRICE_{t-1}) \times 100 \quad (1)$$

ACCY is the forecast accuracy measured by the absolute value of forecast error scaled by the closing stock price in year *t-1* and multiplied by 100 to express the figure in percentage form. This scaling facilitates comparison across firms. $FORECAST_t$ is the most recent mean Institutional Brokers Estimates System (IBES) consensus earnings forecast of year *t* earnings forecast made in the closing month or earlier month of year *t*. EPS_t is the actual earnings per share before extraordinary items in year t, also taken from Institutional Brokers Estimation System (IBES). $PRICE_{t-1}$ is the closing stock price at the end of year *t*.

Earnings Forecast Dispersion

$$DSP_t = (\text{STD}(FORECAST_t) \div PRICE_{t-1}) \times 100 \quad (2)$$

DSP_t is the dispersion of analysts' forecasts in year t defined as the standard deviation of earnings forecast issued by individual analysts. Forecast dispersion can be seen as a measure of the degree of uncertainty about future earnings.

Earnings Forecast Range

$$RANGE_t = ((MAXF_t - MINF_t) \div PRICE_{t-1}) \times 100 \quad (3)$$

$RANGE_t$ is defined as the difference between the maximum and the minimum earnings forecast by individual analyst in year t scaled by the closing stock price in year $t-1$. Similar to DSP, this is also a measure of the uncertainty about future earnings among analysts.

3.2 Measuring Customer Satisfaction

We use the American Customer Satisfaction Index (ACSI) as our measure of customer satisfaction. ACSI has been made available to public by the National Quality Research Center at the University of Michigan's Stephen M. Ross School of Business since 1994. The index is based on surveying customers' opinion using survey questionnaire through telephone and internet, and consistently apply random sampling and the same estimation models across firms and years. The score range from 0 to 100, with larger numbers representing higher customer satisfaction. Its validity and reliability is well documented (e.g. Fornell et al. 1996). The ACSI data has been widely used in marketing, accounting and finance and management studies.

3.3 Measuring Control Variables

All control variables are selected from prior studies. We include firm size (*SIZE* – defined as the natural logarithm of the year end market value) and number of analysts following (*FOLLOW* – defined as the natural logarithm of number of analysts) following

Lang and Lundholm (1996), who find a positive association between firm size, analysts following and forecast accuracy. Hwang et al. (1996) suggest that analysts forecast error is larger on loss firms. We thus include in indicator variable (*LOSS*) for firms that report a negative net income. Following Behn et al. (2008) we add Zmijewski's (1984) financial distress score (*ZMIJ*), who consider financially distressed firms on average have less accurate forecasts. We include earning surprise (*SURPRISE* – defined as the changes in earnings per share deflated by last year's stock price) as Lang and Lundholm report that larger changes in earnings are associated with larger forecast errors. Forecast horizon (*HORIZON* – defined as the natural logarithm of the number of calendar days between the forecast date and the actual earnings announcement date) is included based on Clement et al. (2004) who show that the degree of forecast error is positively associated with forecast horizon in 11 countries. Following Lim (2001), we control for earnings volatility (*STDROE* – defined as the standard deviation of earnings per share before extra-ordinary items in the last five years) as long-term earnings volatility is associated with lower forecast accuracy and more optimistically biased forecasts. As Eames and Glover (2003) document associations between the earnings level and forecast error, we thus include earnings per share (*EL* – defined as the previous year's earnings per share) as a control variable.

We also include indicator variables for calendar year (*YEAR DUMMIES*) to control for the potential fixed effects across time periods. Since 99 percent of our sample firms are audited by "Big 4 auditors" we do not include a control for Big 4 auditors.

3.4 Test Models

To empirically test our three hypotheses **H1**, **H2** and **H3**, we apply the following equation (4), (5) and (6) respectively. All the variables are defined in Table 1. To control for potential heteroscedasticity, we apply White (1980) heteroscedasticity consistent standard errors for all the regression models.

$$ACCY_{j,t} = \delta_0 + \delta_1 ACSI_{j,t} + \delta_2 SIZE_{j,t-1} + \delta_3 SURPRISE_{j,t} + \delta_4 LOSS_{j,t} + \delta_5 ZMIL_{j,t} + \delta_6 HORIZON_{j,t} + \delta_7 STDROE_{j,t} + \delta_8 FOLLOW_{j,t} + \delta_9 EL_{j,t-1} + \textit{Year Dummies} + \varepsilon_{j,t} \quad (4)$$

$$DISP_{j,t} = \Psi_0 + \Psi_1 ACSI_{j,t} + \Psi_2 SIZE_{j,t-1} + \Psi_3 SURPRISE_{j,t} + \Psi_4 LOSS_{j,t} + \Psi_5 ZMIL_{j,t} + \Psi_6 HORIZON_{j,t} + \Psi_7 STDROE_{j,t} + \Psi_8 FOLLOW_{j,t} + \Psi_9 EL_{j,t-1} + \textit{Year Dummies} + \varepsilon_{j,t} \qquad (5)$$

$$RANGE_{j,t} = \Omega_0 + \Omega_1 ACSI_{j,t} + \Omega_2 SIZE_{j,t-1} + \Omega_3 SURPRISE_{j,t} + \Omega_4 LOSS_{j,t} + \Omega_5 ZMIL_{j,t} + \Omega_6 HORIZON_{j,t} + \Omega_7 STDROE_{j,t} + \Omega_8 FOLLOW_{j,t} + \Omega_9 EL_{j,t-1} + \textit{Year Dummies} + \varepsilon_{j,t}$$

(6)

The coefficient of customer satisfaction, δ_1, Ψ_1, and Ω_1 in equations (4), (5) and (6) are our main interest. We expect these three coefficients to be negative and statistically significant, i.e. customer satisfaction is associated with more accurate analysts' earnings forecast, less forecast dispersion, and smaller forecast range.

4. SAMPLE AND EMPIRICAL RESULTS

4.1 Data and Sample

Our sample consists of all U.S. firms with available data for thirteen years from 1995 to 2007. Customer satisfaction data is from ACSI. Analyst annual forecast data is obtained from the Institutional Brokers Estimation System (IBES). We extract actual earnings from IBES to ensure both forecast and actual earnings are stated on the same basis, as IBES makes adjustments to reporting earnings for accounting regularities. To ensure comparability, we use the forecast data made in the closing month of each firm, or the latest forecast data in the month before the closing month if forecast data is not available in the closing month. The accounting data required to construct the control variables are extracted from Compustat. . Our final sample consists of 1,005 firm-year observations. To ensure our results are not driven by outliers, we winsorize all the continuous variables at the 1st and 99th percentiles.

4.2 Sample Characteristics

The descriptive statistics of the regression variables are reported in Table 2. The mean (median) earnings forecast accuracy (*ACCY*) is 1.111 (0.571) in the sample, meaning that the mean (median) difference between the analysts' forecast and the actual earnings per share is about 1.1 (0.6) percent of the lagged share price. The mean dispersion (*DISP*) and mean range (*RANGE*) of 0.182 and 0.587 suggest that the average dispersion and range are 0.18 percent and 0.59 percent of the lagged share price respectively. The mean (median) customer satisfaction (*ACSI*) is 76.356 (76), and is similar to the *ACSI* population (untabulated). The mean *SIZE* is 9.365, and this translates to the average firm total assets being roughly $ 11,665 million, implying that our sample firms are on average large firms. The average earnings surprise (*SURPRISE*) is -0.003. The average *LOSS* is 0.077, suggesting that about 8 percent of the sample observations report negative net income for the year. The mean of *FOLLOW* is 2.725, implying that an average 15 analysts follow a firm in our sample. The mean financial distress score (*ZMIJ*) is -3.437 and the five-year standard deviation return on equity (*STDROE*) is 0.287. In summary, the bivariate correlations suggest that customer satisfaction is associated with higher earnings forecast accuracy, less dispersion and smaller range.

We report the Spearman's rank correlation of the regression variables in Table 3. The three dependent variables *ACCY*, *DISP* and *RANGE* are positively and significantly correlated with each other, suggesting that, as expected, earnings forecast that are more accurate are also less dispersed and have a smaller forecast range. *ACSI* is negatively correlated with *ACCY*, *DISP* and *RANGE* as we expected. All the control variables are significantly correlated with the three dependent variables, and the signs of the coefficients are in line with our expectation. None of the absolute correlation coefficient between ACSI and the control variables exceeds 0.15.

4.3 Regression Results

We perform multivariate analyses using three analysts earnings forecast properties: forecast accuracy (*ACCY*), forecast dispersion (*DISP*), and forecast range (*RANGE*), as dependent variables in equations (4), (5) and (6). Results are reported in Table 4. As a benchmark for comparison, we first report analysis results from the regressions that include only the control variables. The dependent variable in model 1 and 2 is *ACCY*, in model 3 and 4 is *DISP*, and in model 5 and 6 is *RANGE*. It should be noted that models 1, 3 and 5 do not include the *ACSI* variables while the other models do. In model 2, the coefficient of *ACSI* is significantly negative, suggesting that customer satisfaction is associated with higher forecast accuracy. All the control variables have the predicted signs. The coefficient of *SIZE* is negative, showing that larger firms have better information environment. The positive coefficients of *ZMIJ, LOSS, STDROE* and *SURPRISE* suggest that firms with financial distress, report a loss, with high volatility in earnings, and a large change in earnings are less likely to be forecasted accurately. The coefficient of *HORIZON* is positive, implying that the longer the forecast, the lower the forecast accuracy. The coefficients *of FOLLOW* and *EL* are always negative.

The coefficients of *ACSI* in model 4 and 6 are also negative and significant at $p < 0.05$, supporting our hypotheses that customer satisfaction is related to less forecast dispersion and smaller forecast range. The signs of the control variables are similar to that in model 1 and 2.

The adjusted R^2 in model 2 is 0.285, and is 0.014 higher than in model 1, suggesting that *ACSI* has an additional explanatory power in earnings forecast accuracy. Model 4 and 6 also show similar increase in adjusted R^2 by including ACSI as an independent variable.

5. Additional Analyses

5.1 Analysts' Forecast and Cost of Debt Equity

Mansi, Maxwell and Miller (2011) suggest that analysts' forecast accuracy reduces cost of debt. Anderson and Mansi (2009) examine the relation between customer satisfaction and cost of debt and find that higher customer satisfaction firms have lower bond yield spread. To test the moderating role of customer satisfaction in the analysts forecast accuracy/cost of debt relationship, we estimate the following model by inserting both variables and their interaction term into the regression model as follows:

$$IRRP_{j,t} = \beta_0 + \beta_1 ACSI_{j,t} + \beta_2 ACCY_{j,t} + \beta_3 ACSI_{j,t} * ACCY_{j,t} + \beta_4 ROA_{j,t} + \beta_5 GROWTH_{j,t}$$

$$+ \beta_6 LEVERAGE_{j,t} + \beta_7 SIZE_{j,t} + \beta_8 ASSET_{j,t} + \beta_9 RISK_{j,t} + Ind\_dum + Year\_dum + \varepsilon_{j,t} \qquad (7)$$

IRRP is defined as the difference between the firm's annual interest rate (interest expense divided by its average short-term and long-term debt during the year, expressed in percent) and 1-year Treasury bill secondary market rate in year t expressed in percent (source: Federal Reserve). *ROA* is the income before extraordinary items divided by total assets, *GROWTH* is sales revenues minus sales revenues in last year, divided by last year sales revenue, *LEVERAGE* is the sum of total short-term and long-term debt divided by total assets, *SIZE* is natural logarithm of total assets, *ASSET* is net book value of property, plant and equipment divided by total assets, $RISK_{j,t}$ is the standard deviation of the ratio of net income divided by total assets for the last five years, and *Ind_dum* is an indicator variable according to the firm's 1-digit SIC code. Other variables are as defined in Table 1.

Table 5 reports the regression results. The coefficient of the *ACSI* and *ACCY* interaction term is –0.0229, suggesting that the negative association between analysts forecast accuracy and cost of debt is stronger for firms with higher customer satisfaction, i.e. the presence of high customer satisfaction and high analysts' forecast accuracy have a synergy effect to lower a firm's cost of debt. We re-run equation (7) using forecast dispersion (*DISP*) and forecast range (*RANGE*) as proxy for analysts' forecast accuracy. The coefficient of the interaction terms are qualitatively similar to the results reported in Table 5 (untabulated), suggesting the moderating effect of customer satisfaction is not proxy specific.

5.2 Customer Satisfaction and Analysts' Cash Flow Forecast Properties

In addition to earnings forecast, analysts also prepare operating cash flow forecast. For example, IBES first announced cash flow forecast for U.S. firms in 1993. Analysts provide cash flow forecast when the stock market has demand for this information in valuing stocks. Both analyst earnings and cash flow forecasts are used by investors for evaluating firm performance, forming earnings expectations, and determining stock prices. Cash flow information is useful in providing information that complements the earnings information, as cash flows are more objective when compared to earnings that include accruals, which are subjected to management estimates. As a rule, analysts do not just mechanically manipulate earnings to produce cash flow forecast, instead they apply a structured approach and some of them even forecast a full set of financial statements (Call et al., 2009). Defond and Hung (2003) note that the portion of earnings forecasts that also include cash flow forecasts significantly increased from 1% in 1993 to 15% in 1999. They also find that analysts are more likely to issue cash flow forecast for firms with larger accruals, more heterogeneous accounting choices, higher earnings volatility, high capital intensity and weaker financial health. Call, Chen and Tong (2009) indicate that analyst earnings forecasts issued together with cash flow forecasts are more accurate than those not accompanied by cash flow forecast. Their results suggest that analysts that issue both earnings and cash flow forecasts adopt a more structured approach in their work.

Based on similar argument as in the three hypotheses, higher accuracy in predicting future sales due to higher customer satisfaction should enable analysts to reduce errors in cash flow forecasts. Higher customer satisfaction reduces the divergence of beliefs among analysts so that there is less forecast dispersion and the forecast range is smaller. We apply the following equations (8), (9) and (10) to investigate whether customer satisfaction is associated with one- year- ahead cash flow forecasts accuracy, forecasts dispersion and forecast range.

$$CPSACCY_{j,t} = \alpha_0 + \alpha_1 ACSI_{j,t} + \alpha_2 SIZE_{j,t-1} + \alpha_3 SURPRISE_{j,t} + \alpha_4 LOSS_{j,t} + \alpha_5 ZMIL_{j,t} + \alpha_6 HORIZON_{j,t} + \alpha_7 STDCPS_{j,t} + \alpha_8 FOLLOW_{j,t} + \alpha_9 OP\_CYCLEL_{j,t} + \alpha_{10} EL_{j,t-1} + Year\ Dummies + \varepsilon_{j,t} \quad (8)$$

$$CPSDISP_{j,t} = \mu_0 + \mu_1 ACSI_{j,t} + \mu_2 SIZE_{j,t-1} + \mu_3 SURPRISE_{j,t} + \mu_4 LOSS_{j,t} + \mu_5 ZMIL_{j,t} + \mu_6 HORIZON_{j,t} + \mu_7 STDCPS_{j,t} + \mu_8 FOLLOW_{j,t} + \mu_9 OP\_CYCLEL_{j,t} + \mu_{10} EL_{j,t-1} + Year\ Dummies + \varepsilon_{j,t}$$

(9)

$$CPSRANGE_{j,t} = \omega_0 + \omega_1 ACSI_{j,t} + \omega_2 SIZE_{j,t-1} + \omega_3 SURPRISE_{j,t} + \omega_4 LOSS_{j,t} + \omega_5 ZMIL_{j,t} + \omega_6 HORIZON_{j,t} + \omega_7 STDCPS_{j,t} + \omega_8 FOLLOW_{j,t} + \omega_9 OP\_CYCLE_{j,t} + \omega_{10} EL_{j,t-1} + Year\ Dummies + \varepsilon_{j,t} \quad (10)$$

CPSACCY is the cash flow forecasts accuracy measured by the absolute value of forecast error scaled by the closing stock price in year *t-1* and multiplied by 100 to express the figure in percentage form. This scaling facilitates comparison across firms. $CPSFORECAST_t$ is the most recent mean Institutional Brokers Estimates System (IBES) consensus cash flow forecast of year t earnings forecast made in the closing month or earlier month of year t. $CPS_{t\ t}$ is the actual cash flow from operation in year t, also taken from IBES. $PRICE_{t-1}$ is the closing stock price at the end of year *t*.

$CPSDISP_t$ is the dispersion of analysts' forecasts in year *t* defined as the standard deviation of cash flow forecast issued by individual analysts. Forecast dispersion can be seen as a measure of the degree of uncertainty about future earnings. $CPSRANGE_t$ is defined as the difference between the maximum and the minimum cash flow forecast by individual analyst in year *t* scaled by the closing stock price in year *t-1*. Similar to *CPSDSP*, this is also a measure of the uncertainty about future earnings among analysts.

STDCPS is the standard deviation of operating cash flow per share in the last five years, as long-term earnings volatility should be more difficult to forecast accurately. Following Barth et al. (2001) who suggest that the predictive power of accruals for future cash flows depends on firm's operating cycle, we add *OP_CYCLE* (operating cycle measured as the sum of days accounts receivable and days inventory deflated by 365 to express it as a fraction of a year) in our regression models. The other control variables are similar to the ones in the earnings forecast models in equations (4) to (6). We expect the coefficient of customer satisfaction, α_1, μ_1, and ω_1 in equations (8), (9) and (10) to be negative and statistically significant, i.e. Customer satisfaction is associated with more accurate analysts' cash flow forecast, less cash flow forecast dispersion and smaller cash flow forecast range.

Our sample consists of U.S. firms from 2000 to 2007, as there are only a few observations in each year from year 1994 to 1999. We report the regression results in Table 5. Models 1, 3 and 5 do not include the *ACSI* variables while the other models do. In model 2, the coefficient of *ACSI* is -0.103 and is significantly at the 0.01 level, suggesting that customer satisfaction is associated with more accurate cash flow forecast. All the control variables have the predicted signs.

The coefficients of *ACSI* in models 4 and 6 are negative (-0.097 and -0.162 respectively) and significant at $p < 0.01$, supporting our conjecture that customer satisfaction is related to less cash flow forecast dispersion and smaller cash flow forecast range. The signs of the control variables are similar to that in model 1 and 2. The adjusted R^2 in model 2 is 0.264 and is 0.048 higher than in model 1, showing that model 2 has better explanatory power in the variation of analysts' cash flow forecast accuracy by including customer satisfaction as test variable. Similarly, the adjusted R^2 of model 4 and 6 with customer satisfaction as test variable are 0.095 and 0.091 higher than the adjusted R^2 of model 3 and 5.

5.3 Customer Satisfaction and Other Years' Analysts' Forecast Properties

In our main tests, we use the Year t analysts forecast data to show that customer satisfaction is associated with higher forecast accuracy, less dispersion and smaller range. We also examined whether customer satisfaction is related to later year forecast properties. We re-run equations (4), (5) and (6) using the Year t+1 and Year t+3 analysts' forecast data. The regression results are qualitatively similar to our main results reported in Table 4 (untabulated), and the signs of the control variables are as predicted. We also re-estimate equations (8), (9) and (10) using the Year t+1 and Year t+2 analyst cash flow forecast data in IBES. The results are generally similar as in Table 6.

In summary, our results suggest that customer satisfaction is associated with more accurate future earnings and cash flow forecast accuracy, less forecast dispersion and smaller forecast range.

5.4 Control for Unobserved Firm-Level Fixed Effect

Although we have included several control variables that are known to affect analysts' forecast properties, our findings may still be influenced by unobserved firm-level heterogeneity. As an additional test, we use hierarchical linear modelling (HLM) to cater for potential unobserved firm level effects (Raudenbush and Bryk, 2002). We re-estimate equations (4), (5), and (6) with an HLM approach. The results are qualitatively similar to our main results reported in Table 4. We report the HLM results in Table 6. As shown in models 2, 4 and 6 the coefficients of *ACSI* are negative with p-values < 0.01. The coefficients of *Akaike's Information Criterion (AIC)* and *Schwarz's Bayesian Criterion (BIC)* become smaller by adding *ACSI* as an independent variable, suggesting that ACSI has explanatory power in the variation of analysts' earnings forecast properties. In summary, the HLM results support our three hypotheses. We also re-estimate equations (8), (9) and (10) with a HLM approach, the results (untabulated) show that our findings reported in Table 6 are not limited to the use OLS methods.

6. Sensitivity Analysis

We perform a number of sensitivity tests to assess the robustness of our findings. *First*, we reduce the effect of forecast horizon by following Behn et al. (2008) and use the IBES forecast data of year *t* made during the period starting two months before the actual earnings announcement and ending three days before the results announcement. *Second*, we substitute ZMIJ with Altman's Z-score to control for financial distress. *Third*, we use natural logarithm of total assets to replace natural logarithm of market value as proxy for size. None of these re-specifications in sampling, deflators, control variables and estimation models substantially affect our main results as presented in Table 4, indicating that the main results are not model specific and not driven by some particular observations.

7. Conclusion

In this paper we examine whether customer satisfaction is associated with more accurate analyst earnings forecast and cash flow forecast, less forecast dispersion and smaller forecast range. We conjecture that the sustainable future sales revenue and operating cash flow generated by high customer satisfaction enables analysts to make more accurate forecast of future revenue. Our results show that higher level of customer satisfaction is associated with improved accuracy in analyst earnings and cash flow forecasts. These findings hold after we control for previously identified determinants that affect analyst forecast properties. We thus conclude that firm-level customer satisfaction is a significant determinant of analyst forecasts accuracy.

Intangible marketing assets like customer satisfaction are taking an increasing larger portion of firm value. Current accounting system requires investment in marketing to be expensed immediately instead of being capitalized. If customer satisfaction, partially resulted from marketing expenditure, is positively associated with forecasts accuracy, regulators and standard setters may consider improving disclosure about it so that stakeholders can make more informed decision.

There are some potential caveats in this study. *First*, while our results suggest a link between customer satisfaction and analyst forecast properties, we do not claim a causal relationship between them. Although we show that customer satisfaction is associated with current year forecast properties as well as other years forecast properties, we also cannot rule out the possibility that some unknown omitted factors drive customer satisfaction and the analyst forecast properties. Second, since our sample firms are large US firms, we cannot generalize our findings to smaller companies and to firms in other countries. We leave this to future research in this area. Despite these limitations, our study provides some insights for marketing managers on the link between customer satisfaction and analyst forecasts properties. Such evidence contributes to both the marketing and the finance literature.

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Table 1
Description of Variables

Variables	Expected Sign	Definitions
Dependent variables		
$ACCY_{j,t}$		Analyst earnings forecast accuracy of firm *j* in year *t*
$DISP_{j,t}$		Analyst earnings forecast dispersion of firm *j* in year *t*
$RANGE_{j,t}$		Analyst earnings forecast range of firm *j* in year *t*
$CPSACCY_{j,t}$		Analyst cash flow forecast accuracy of firm *j* in year *t*
$CPSDISP_{j,t}$		Analyst cash flow forecast dispersion of firm *j* in year *t*
$CPSRANGE_{j,t}$		Analyst cash flow forecast range of firm *j* in year *t*
Test variable		
$ACSI_{j,t}$	Negative (-)	A measure of customer satisfaction conducted by the University of Michigan's Ross School of Business.
Control variables		
$SIZE_{j,t}$	Negative (-)	Natural logarithm of the opening market capitalization of firm *j* in year *t*.
$SURPRISE_{j,t}$	Positive (+)	the changes in earnings per share of firm *j* in year *t* deflated by closing stock price in year *t-1*
$ZMIJ_{j,t}$	Positive (+)	Zmijewski's (1984) financial distress score, the higher the value imply higher financial distress
$HORIZON_{j,t}$	Positive (+)	Natural logarithm of the number of calendar days between the forecast date and the actual earnings announcement date
$STDROE_{j,t}$	Positive (+)	The standard deviation of earnings per share before extra-ordinary items in the last five years
$STDCF_{j,t}$	Positive (+)	The standard deviation of operating cash flow per share in the last five years
$FOLLOW_{j,t}$	Negative (-)	the natural logarithm of number of analysts following firm j and issue analyst forecast
$EL_{j,t-1}$	Not Clear-cut	Firm *j*'s earnings per share in year *t-1*
$OP\_CYCLE_{j,t}$	Positive (+)	The sum of days accounts receivable and days inventory divided by 365 days
Year Dummies	Not Clear-cut	Indicator variable for year to control for potential fixed effect

Table 2
Descriptive Statistics

Variable	Mean	Median	St. Dev.	25th Percentile	75th Percentile
ACCY	1.111	0.571	1.549	0.291	1.172
DISP	0.182	0.068	0.935	0.032	0.149
RANGE	0.587	0.248	2.645	0.117	0.533
ACSI	76.356	76	6.095	73	81
SIZE	9.365	9.337	1.275	8.521	10.147
SURPRISE	-0.003	0.006	0.093	-0.012	0.015
LOSS	0.077	0.000	0.266	0.000	0.000
ZMIJ	-3.437	-3.343	0.991	-4.047	-2.869
HORIZON	3.418	3.401	0.406	3.178	3.689
STDROE	0.287	0.058	0.876	0.026	0.141
FOLLOW	2.725	2.833	0.541	2.398	3.135
EL	1.838	1.690	1.202	1.116	2.530

Note: This table reports the summary statistics for the1,005 firm-year observations over the period 1994 - 2007. For variable definitions please refer to Table 1.

Table 3
Bivariate Correlations

Variable	*DISP*	*RANGE*	*ACSI*	*SIZE*	*SURPRISE*	*LOSS*	*ZMIJ*	*HORIZON*	*STDROE*	*FOLLOW*	*EL*
ACCY	.632**	.681**	-.165**	-.192**	.087**	.300**	.185**	.147**	.377**	-.124**	-.210**
	(0.000)	(0.000)	0.000	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DISP		.980**	-.180**	-.190**	.125**	.266**	.211**	.127**	.218**	-.147**	-.201**
		0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RANGE			-.214**	-.176**	.123**	.270**	.221**	.123**	.243**	-.099**	-.199**
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
ACSI				0.002	-.084**	-.132**	-.108**	0.022	-0.043	-0.048	.090**
				(0.945)	(0.007)	(0.000)	(0.001)	(0.493)	(0.172)	(0.128)	(0.004)
SIZE					-0.033	-.247**	-.278**	-.310**	-.131**	.514**	.259**
					(0.298)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SURPRISE						-.122**	0.027	-0.051	.194**	-0.024	-0.028
						(0.000)	(0.396)	(0.109)	(0.000)	(0.447)	(0.372)
LOSS							.263**	.132**	.190**	-.078*	-.308**
							(0.000)	(0.000)	(0.000)	(0.014)	(0.000)
ZMIJ								.151**	.344**	-.153**	-.084**
								(0.000)	(0.000)	(0.000)	(0.008)
HORIZON									.139**	-.441**	-.104**
									(0.000)	(0.000)	(0.001)
STDROE										-.096**	-.191**
										(0.002)	(0.000)
FOLLOW											-0.030
											(0.349)

*Note: This table reports the Spearman's rank correlation between the regression variables for the 1,005 firm-year observations over the period 1994 - 2007. ***, **, * indicate bivariate coefficient significance at the 0.01, 0.05 and 0.10 level respectively. P-values (two-tailed) are reported in parentheses. For variable definitions please refer to Table 1.*

Table 4
OLS Regression results of the association between customer satisfaction and analyst earnings forecast properties

Variable	Expected Sign	Dependent Variable: *ACCY* Model 1		Model 2		Dependent Variable: *DISP* Model 3		Model 4		Dependent Variable: *RANGE* Model 5		Model 6	
Intercept	?	5.173	**	13.673	**	1.309	*	2.846	**	2.902		8.098	**
ACSI	–			-0.118	**			-0.021	**			-0.073	**
SIZE	–	-0.119	*	-0.086	*	-0.013		-0.005		-0.094	**	-0.069	*
SURPRISE	+	3.971		3.532		1.181		1.050		3.159		2.716	
LOSS	+	4.652	***	4.426	***	0.696	***	0.646	***	1.958	***	1.790	***
ZMIJ	+	0.095		0.003		0.103		0.089		0.304		0.258	
HORIZON	+	0.127	**	0.193	*	0.020	**	0.033	*	0.150	**	0.193	**
STDROE	+	1.974	*	2.000	*	0.096		0.105		0.348		0.378	
FOLLOW	–	-0.996	**	-1.230	**	-0.167	*	-0.208	**	-0.072		-0.211	
EL	?	-0.450	**	-0.394		-0.088		-0.078		-0.217		-0.185	
Year Dummies		Yes		Yes		Yes		Yes		Yes		Yes	
Adjusted R^2		0.271		0.285		0.145		0.163		0.148		0.173	
Sample size		1,005		1,005		1,005		1,005		1,005		1,005	

*Note: Dependent variables are analyst earnings forecast accuracy, dispersion and range respectively. ***, **, * indicate explanatory variable coefficient significance at the 0.01, 0.05 and 0.10 level respectively. All significance values are White adjusted. For variable definitions please refer to Table 1.*

Table 5
Regression Results of the Moderating Effect of Customer Satisfaction in the Analysts' Forecast Accuracy/Cost of Debt Negative Relationship

Variable	Expected Sign	Model 1		Model 2		Model 3	
Intercept	?	0.2322	***	0.0438	***	0.21	***
ACSI	−	-0.0426	***			-0.0377	***
ACCY	+			0.0032	***	0.0978	***
*ACSI*ACCY*	?					-0.0229	***
ASSET	−	-0.0025		-0.0031		-0.0026	
LEVERAGE	−	-0.0186	***	-0.0159	***	-0.0188	***
ROA	−	-0.0123		-0.0092		-0.0078	
SIZE	−	-0.0048	***	-0.0045	***	-0.0047	***
GROWTH	?	0.0080		0.0076		0.0079	
RISK	+	-0.0049		0.0128		-0.0020	
Year Dummy		Yes		Yes		Yes	
Industry Dummy		Yes		Yes		Yes	
Adjusted R^2		0.480		0.477		0.485	
Sample size		1005		1005		1005	

*Dependent variable is interest rate risk premium IRRP. ***, **, * indicate explanatory variable coefficient significance at the 0.01, 0.05 and 0.10 level respectively. All significance values are White adjusted.*

Table 6

OLS regression results of the association between customer satisfaction and analyst cash flow forecast properties

	Predicted	Dependent Variable: *CPSACCY*				Dependent Variable: *CPSDISP*				Dependent Variable: *CPSRANGE*			
Variable	Sign	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Intercept	?	13.090	***	21.501	***	-0.001		7.960	***	-2.624		10.690	***
ACSI	–			-0.103	***			-0.097	***			-0.162	***
SIZE	–	-0.728	**	-0.785	***	-0.111		-0.165		-0.084		-0.174	
SURPRISE	+	-7.903	*	-9.177	**	0.655		-0.551		2.764		0.748	
LOSS	+	2.429		1.884		1.682	**	1.166	*	3.492	***	2.628	**
ZMIJ	+	0.516		0.472		0.198		0.156		0.470	**	0.400	*
HORIZON	+	-0.796		-0.803		0.737	**	0.730	**	1.332	**	1.320	**
STDCF	+	24.278	**	20.778	**	2.563		-0.750		11.734		6.193	
FOLLOW	–	-0.057		-0.167		-0.019		-0.123		1.764	**	1.589	***
EL	?	-0.011		-0.108		-0.229	*	-0.138		-0.379	*	-0.227	
OP_CYCLE	+	3.023		4.095		-0.873		0.142		-1.369		0.329	
Year Dummies		Yes		Yes		Yes		Yes		Yes		Yes	
Adjusted R^2		0.216		0.264		0.162		0.257		0.243		0.334	
Sample size		198		198		198		198		198		198	

*Note: Dependent variables are analyst cash flow forecast accuracy, dispersion and range respectively. ***, **, * indicate explanatory variable coefficient significance at the 0.01, 0.05 and 0.10 level respectively. All significance values are White adjusted. For variable definitions please refer to Table 1.*

Table 7

HLM regression results of the association between customer satisfaction and analysts' earnings forecast properties

Variable	Predicted Sign	Dependent Variable: *ACCY* Model 1		Model 2		Dependent Variable: *DISP* Model 3		Model 4		Dependent Variable: *RANGE* Model 5		Model 6	
Intercept	?	3.696	***	6.119	***	0.435	***	0.848	***	0.831	***	2.363	***
ACSI	–			-0.031	***			-0.005	***			-0.020	***
SIZE	–	-0.079		-0.102	*	-0.025	***	-0.027	***	-0.073	***	-0.081	***
SURPRISE	+	-0.254		-0.371		0.119	**	0.098	*	0.259	*	0.189	
LOSS	+	1.109	***	1.109	***	0.112	***	0.113	***	0.388	***	0.381	***
ZMIJ	+	0.052		0.030		0.003		-0.001		0.014		0.004	
HORIZON	+	0.030		0.024		0.030	*	0.029	*	0.116	**	0.112	**
STDCF	+	0.341	***	0.338	***	0.023	***	0.022	***	0.094	***	0.092	***
FOLLOW	–	-0.575	***	-0.556	***	-0.046	***	-0.045	***	0.007		0.010	
EL	?	-0.185	***	-0.176	***	-0.023	***	-0.021	***	-0.052	***	-0.041	**
2 Log Likelihood		3,147.6		3,145.0		203.8		201.1		2,342.9		2,330.5	
Akaike's Information Criterion (AIC)		3,177.6		3,175.0		233.8		231.1		2,372.9		2,360.5	
Schwarz's Bayesian Criterion (BIC)		3,251.2		3,248.6		307.4		304.6		2,446.5		2,434.0	
Sample size		1,005		1,005		1,005		1,005		1,005		1,005	

*Note: Dependent variables are analyst cash flow forecast accuracy, dispersion and range respectively. ***, **, * indicate explanatory variable coefficient significance at the 0.01, 0.05 and 0.10 level respectively. For variable definitions please refer to Table 1.*