2017

# Favorability of Financial and Nonfinancial Performance Measures and Analysts' Recommendations

Thomas F. Lewis Jr
*Virginia Commonwealth University*

**Favorability of Financial and Nonfinancial Performance Measures and Analysts' Recommendations**

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

by

Thomas F. Lewis, Jr., CPA
Doctor of Philosophy
Accounting Department, School of Business
Virginia Commonwealth University

Director: Benson Wier, Ph.D.
Dean's Scholar Professor of Accounting
Accounting Department, School of Business
Virginia Commonwealth University

Virginia Commonwealth University
Richmond, Virginia
April 13, 2017

Table of Contents

List of Tables

Abstract

FAVORABILITY OF FINANCIAL AND NONFINANCIAL PERFORMANCE MEASURES AND ANALYSTS' RECOMMENDATIONS

By Thomas F. Lewis, Jr., Ph.D., CPA

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

Virginia Commonwealth University, 2017.

Major Director: Benson Wier, Ph.D., Dean's Scholar Professor of Accounting

This study investigates the extent to which sell-side analysts make full use of available financial and nonfinancial information signals in formulating stock recommendations. Prior research shows that investors rely strongly on sell-side analysts' recommendations and that sell-side analysts pay considerable attention to nonfinancial measures in making their decisions. However, prior research has primarily focused on the mere presence of nonfinancial measures and not the extent to which the direction of such measures (i.e. favorability) is associated with firm value, or assessed the extent to which any interaction between financial measures and the

direction of nonfinancial measures may influence analysts in formulating stock recommendations. Using a data set hand-collected from annual proxy statements, I use ordered logistic regression analysis to provide a multivariate test of the relation between sell-side analyst recommendations, financial and context-specific nonfinancial measures. I find that analysts do incorporate the direction (favorability) of nonfinancial measures in formulating stock recommendations and that unfavorable nonfinancial measures attenuate positive financial information.

# INTRODUCTION

This study investigates the extent to which sell-side analysts make full use of available financial and nonfinancial information signals in formulating stock recommendations. Sell-side analysts' recommendations are the end-product from an extensive analysis of information; however, the introduction of new technology, globalization and the transition towards a knowledge based economy have decreased the value relevance of financial statement information and have forced interested parties to seek out information beyond the financial statements to judge firm value (Amir and Lev 1996; Ittner and Larcker 1998a; Lev and Zarowin 1999; Liang and Yao 2005). Prior research shows that investors rely strongly on sell-side analysts' earnings forecasts, recommendations and reported information (Hirst, Koonce and Simko 1995; Ackert, Church and Shehata 1996; Womack 1996) and that sell-side analysts pay considerable attention to nonfinancial measures in making their decisions (Dempsey, Gatti, Grinell and Cats-Baril 1997; Low and Siesfield 1998; Breton and Taffler 2001). However, prior research has primarily focused on the mere presence of nonfinancial measures and not the extent to which the direction of such measures (i.e. favorability) are associated with firm value. What are the implications when a company reports positive financial information but fails to meet established nonfinancial benchmarks or vice versa? This study assesses the extent to which sell-side analysts consider the interaction between financial data and the direction nonfinancial measures in formulating stock recommendations.

Prior research in psychology implies that negative information possesses greater diagnostic value (Skowronski and Carlston 1989) and elicits more cognitive analysis (Taylor 1991) than positive information, which suggests that individuals place greater reliability and reliance on negative information. The corollary of these findings is that positive information is perceived to be less diagnostically-valuable and receives less cognitive analysis. I examine whether this holds true for sell-side analysts when presented with both financial and nonfinancial information with contrariant content. The question is worth examining since firms are disclosing nonfinancial information more than ever before, and serves to highlight the source of the investment value provided by sell-side analyst's stock recommendations. Are sell-side analysts adding value through the collection and processing of both financial and nonfinancial information useful in identifying undervalued or overvalued stocks, or are sell-side analysts' recommendations more inclined towards stocks with specific financial characteristics that predict future returns?

I expect this research to be of interest to both academics and practitioners. From an academic perspective, the study contributes to the stream of nonfinancial performance literature by providing a better understanding of the predictive value of nonfinancial performance measures. It also contributes to a better understanding of how sell-side analysts evaluate stocks and their role in the price formation process. From the perspective of investors, this research enhances the understanding of the usefulness (limitations) of both nonfinancial performance measures and sell-side analyst recommendations in investment decisions. Finally, from the perspective of the sell-side analyst, this study provides another potential decision aid for making better recommendations (at least in terms of improved returns prediction).

I begin my study by clearly defining the setting. Selecting the proper setting in which to evaluate nonfinancial measures is key to identifying the effects. Despite the increasing importance of nonfinancial information, prior research finds nonfinancial information is hard to mandate and to standardize due to the firm- and industry-specific nature of nonfinancial information, the disclosure costs (e.g. competitive costs) and the risk of receiving vague and uninformative disclosure (Skinner 2008; Stark 2008). To capitalize on the opportunities presented in examining nonfinancial information, I have selected the setting of executive compensation, specifically executive compensation contracts.

Although, the objective of compensation-based contracts is to align managers' interests with those of shareholders, inappropriately constructed compensation contracts may result in unintended outcomes when actions taken by managers result in wealth reduction for shareholders (Fields, Lys and Vincent 2001). To deal with this concern, companies have introduced nonfinancial performance measures (*NFM*) into executive compensation contracts. The intent is to increase shareholder value through the creation of a "balanced scorecard." The "balanced scorecard" offsets short-term focused financial incentives with long-term focused nonfinancial incentives which, in theory, create a better alignment between the interest of management (i.e. what's best for me, now) and shareholders (i.e. what's best for the firm, long run). Therefore, executive compensation contracts provide a unique environment (across many firms/industries) to observe management incentives motivated by both financial and nonfinancial benchmarks. In addition, detailed executive compensation information, for publicly traded companies, is available annually through the proxy statement filing.[1]

Using panel data from a population of firms who have appeared in the S&P 500 Index at least once in the period 2000-2013, I first examine annual proxy statements and document each firm's utilization of *NFM* in the compensation contract of the CEO based on a keyword search.

[1] A proxy statement, containing executives' compensation (including salaries, bonuses, equity awards and any deferred compensation) must be filed by a publicly traded company before shareholder meetings. State laws require that publicly held companies hold shareholder meetings on an annual basis and most publicly traded companies hold annual meetings soon after the close of their fiscal year to facilitate a discussion of financial performance over the previous twelve months.

Second, I identify the direction (i.e. favorability) of each nonfinancial performance measure in comparison to a predefined target from the annual proxy statement. Third, I collect consensus analysts' recommendations and the corresponding financial data. Fourth, I use ordered logistic regression analysis to provide a multivariate test of the relation between the analyst recommendations, the financial and nonfinancial data to assess the extent to which sell-side analysts consider the context and predictive nature of each type of data (financial and nonfinancial), and their interactive effect, when making stock recommendations. I find that analysts do incorporate the direction (favorability) of nonfinancial measures in formulating stock recommendations and that unfavorable nonfinancial measures attenuate positive financial information.

The remainder of the paper is organized as follows. In Section II, I discuss previous literature and generate my hypotheses. Section III and IV outline my research design and present the findings, respectively. Section V details additional analyses and Section VI robustness tests. Section VII provides my conclusions.

## LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

### Analysts, Recommendations and Stock Characteristics

Corporate monitoring, information production and dissemination are important functions of sell-side financial analysts' activities. Prior studies have concluded that the information sell-side analysts produce promotes market efficiency by helping investors to more accurately value companies (Schipper 1991; Brown 2000). Sell-side analysts gather and process a variety of information about different stocks, form their beliefs about the intrinsic stock values relative to their current market prices, and finally rate the investment potential of each stock. As Elton, Gruber, and Grossman (1986, p. 699) observe, sell-side analyst stock recommendations represent "one of the few cases in evaluating information content where the forecaster is recommending a clear and unequivocal course of action rather than producing an estimate of a number, the interpretation of which is up to the user."

It is commonly believed that a recommendation is the analyst's way of communicating beliefs about future stock performance. For example, a "buy" ("sell") recommendation may indicate the belief that the stock is under (over)-valued and is, thus, expected to generate positive (negative) future abnormal returns. Francis and Soffer (1997) state that hold recommendations, taken at face value imply that the stocks are fairly priced but they also explain that the skewed distribution of recommendations suggests that holds should not be taken at face value. To truly assess the value of analyst recommendations in investment decisions, the selection of stock characteristics that have demonstrated abilities to predict future returns is required (Drake, Rees and Swanson 2011). Prior research highlights variables (comprised of quantitative financial data) that are predictors of future stock performance and that are commonly used by analysts in their valuations.[2] Which is the basis for Hypothesis 1a, stated as follows:

**Hypothesis 1a. Financial performance is positively associated with analyst recommendations.**

## Performance Consequences of Nonfinancial Measures

The informativeness principle (Holmstrom 1979; Banker and Datar 1989; Feltham and Xie 1994) is the foundation of a large body of research that examines the implications of agency theory on the trade-off between risk and incentives. Compensation contracts should include performance measures that provide incremental information about the dimensions of managerial action that the shareholders wish to encourage (Ittner and Larcker 1997). The inclusion of nonfinancial measures in compensation contracts more closely align manager effort along the dimensions emphasized by those measures, resulting in improvements in performance (Banker, Potter, and Srinivisan 2000). HassabElnaby, Said and Wier (2005) findings support the contention that firms that employ a combination of financial and nonfinancial performance measures have significantly higher mean levels of returns on assets and higher levels of market returns.

Several additional studies suggest that nonfinancial measures are primarily important because they focus management on long-term actions, such as innovation and quality, which leads to better future performance (Kaplan and Norton 1992; Hemmer 1996; Banker et al. 2000). Consistent with these claims, several studies find that nonfinancial performance measures are leading indicators of financial performance, even after controlling for current accounting

[2] See the Appendix for a detail listing of predictor variables of future stock performance (definitions and citations).

performance (Foster and Gupta 1997; Behin and Riley 1999; Banker et al. 2000).

### Relevance of Nonfinancial Disclosure

One approach to determining the relevance of corporate nonfinancial information is to examine the impact of nonfinancial disclosure on the quality of sell-side financial analysts' earnings estimates. Vanstraelen, Zarzeski and Robb (2003) find a positive association between sell-side financial analysts' earnings forecast accuracy and forward-looking disclosure. Barron, Kile and O'Keefe (1999) demonstrate that better quality information included in the Management Discussion and Analysis enhances the accuracy of the sell-side analysts' earnings forecasts. These findings support Opdyke's (2000) argument that a strong focus by sell-side financial analysts on financial data does not yield accurate earnings forecasts. Orens and Lybaert (2007) show that sell-side financial analysts using more forward-looking information, as well as information about innovation and research and development, make smaller errors in estimating future earnings. These results confirm the survey findings of Epstein and Palepu (1999) and Eccles, Herz, Keegan and Phillips (2001) showing that financial statements are insufficient for meeting sell-side financial analysts' information needs. Which is the basis for Hypothesis 1b, stated as follows:

**Hypothesis 1b. The presence of nonfinancial performance measures is positively associated with analyst recommendations.**

### Direction of Performance Measures

Psychology research on attribution and persuasion suggests that the perceived credibility of management's communications depends on users' ex ante expectations of management's messages and whether management's message confirms or disconfirms the expectation (Eagly and Chaiken 1975; Fiske and Pavelchak 1986). Thus, regarding performance measures' favorableness, since there is a tendency by management to provide a greater number of overly positive disclosures than overly negative disclosures (McNichols 1989), unfavorable or negative outcomes are regarded as more credible and have a greater impact than favorable or positive outcomes disclosure, ceteris paribus (Mercer 2005).

The differential reaction to negative/positive outcomes is consistent with prospect theory which suggests that investors are more sensitive to losses than gains (Kahneman and Tversky 1979) and in making judgments, the negative aspects of an event or a message are weighted more heavily than the positive aspects (Kahneman and Tversky 1984; Peeters and Czapinski 1990). Evidence from archival research supports this claim. For example, disclosures of unfavorable news result in larger analyst forecast revisions (Hassell, Jennings and Lasser 1988; Williams 1996) and stock price reactions (Cairney and Richardson 1998; Hutton, Miller and Skinner 2003) than disclosures of favorable news. Further, there are marked differences in the accuracy and bias of analysts' earnings forecast for loss making (i.e., unfavorable) firms than for non-loss (i.e., favorable) firms (Das 1998). That is, even professionals react more to losses or negative information compared to gains or positive information (Anderson 1988).[3]

Accounting research shows that when a measure is favorable, supporting or additional information increases the measure's credibility. For example, favorable earnings forecasts are more likely to result in stock price movements when the forecasts are accompanied by supporting information such as sales forecasts and profit margins (Gigler 1994; Cairney and Richardson 1998; Hutton et al. 2003). In contrast, unfavorable news forecasts result in stock price movements regardless of whether they are accompanied by supporting information. Hutton

[3] Other studies in psychology evaluated the different cognitive processes observed when individuals respond to unfavorable information. Skowronski and Carlston (1989) suggested that unfavorable information is perceived to be more diagnostic; thus, individuals adopt a more negative bias in light of such information. Unfavorable events prompt more cognitive analysis (Taylor 1991), narrowing the focus of attention on factors that cause the unfavorable state (Broadbent 1971). Marketing research finds consumers are more sensitive to decreases in perceived quality compared to increases in perceived quality (Anderson and Salisbury 2003).

et al. (2003) suggest that a likely reason for the interaction of favorable forecasts and supporting information, but not for unfavorable forecasts and supporting information is because unfavorable news is inherently more credible to investors or analysts than favorable news. Hence, unfavorable news does not require additional supporting information to increase its credibility.

The same argument may be extended to the interaction of financial/nonfinancial measures and favorable/unfavorable outcomes. For example, when financial measures are unfavorable, their impact on sell-side analysts' decisions should be significant and invariant with the favorableness of nonfinancial measures. However, if the financial measures are favorable, then nonfinancial measures are supporting information and should have a differential impact on analysts' recommendations depending on the direction of the measures. The above discussion is the basis for the Hypothesis 1c, stated as follows:

**Hypothesis 1c. When nonfinancial performance is unfavorable, the association between financial performance and analyst recommendations is weaker than when nonfinancial performance is favorable.**

## RESEARCH DESIGN

### Sample and Data

To perform my analysis, I require data on analyst recommendations, open short positions, 11 financial predictor variables, stock returns and nonfinancial performance. I obtain analyst recommendations from the Thompson Financial I/B/E/S Recommendations database. I/B/E/S provides analyst recommendations for a wide cross-section of firms. I obtain open short positions from the Compustat Monthly Securities database, which will be used in the supplemental analysis. I obtain quarterly financial data from Compustat Quarterly Securities database and nonfinancial performance data from DEF-14A statements in the Edgar on-line database. I obtain stock returns data from the CRSP database.

My final sample, resulting from the intersection of Compustat, CRSP, I/B/E/S, and my hand-collected data, consists of 23,534 firm-quarter observations over the 52 calendar quarters from 2000 to 2013. For my main analysis, I rank firms into quintiles based on analyst recommendations (both levels and changes), and for my supplemental analysis, short interest in each calendar quarter t. For recommendation changes, I ensure that firms without a recommendation revision are included in the middle quintile.

Table 1, Panel A presents descriptive statistics for the variables used in my analyses. The mean (median) value for *Rec* of 3.66 (3.68) indicates that the average analyst recommendation is only moderately less than a “buy” (which would be coded 4). A narrow interquartile range of 0.15 (—0.09 to 0.06) for the consensus recommendation change, *ChgRec*, shows that analyst recommendations are generally sticky. Nevertheless, the minimum and maximum values for *ChgRec* indicate that analysts occasionally downgrade a stock all the way from strong buy to hold, and vice versa. The mean short interest ratio, *SIratio*, is 3.6 percent, which is considerably larger than the median of 2.3 (due to some large values, as indicated by the maximum of 46.2 percent). With respect to the 11 predictor variables, I find that earnings surprise (*SUE*) has a mean of 0.04, consistent with most firms reporting earnings that meet or beat the current analyst forecast. On average, total accruals (*TACCR*) are positive. Capital expenditures (*CAPEX*) average approximately 12 percent of assets. I find that firm size (*MVE*) is highly skewed, with a mean of $19,901 compared to a median of $8,311 (in millions). The average earnings-to-price ratio (*EP*) is only 3.0 percent due to some negative values (median 5.0 percent). The book-to-market ratio (*BTM*) has a mean of 0.45 (median 0.36), consistent with prior research. Approximately 0.09 percent of a firm's shares turn over on any given day (*TURN*). Realized sales growth (*SG*) averages 15 percent, and analysts' long-term earnings growth forecasts (*LTG*) average 13.11 percent. Analysts' forecast revisions (*FREV*) have a mean and median of zero. Price momentum (*MOM*) averages 1.0 percent for the preceding six months (median 1.0 percent).

[insert Table 1]

Table 1, Panel B reports mean analyst recommendations and short interest for each year from 2000 to 2013. Beginning in 2000, I observe a peak in the average analyst recommendation followed by declines in years 2001 through 2003, and then a monotonic increase through the end of my test period. This shift corresponds with criticism of analysts that led to the Global

Research Analysts Settlement, NASD 2711, and NYSE Rule 472. One line of criticism focused on analysts' conflicts of interest, including their incentive to maintain a positive relation with corporate managers to generate investment banking business and to obtain earnings guidance.

Table 1, Panel B also reports another noteworthy change over my test period. The mean level of short interest is around 2 percent in 2000. The level then increases appreciably over the next eight years, reaching a high of 5.0 percent in 2008 before decreasing throughout the final year of the sample period. This shift, which corresponds with a dramatic increase in the number of hedge funds and the financial crisis, increases the importance of research that furthers an understanding of the role of short selling in the price formation process. Note that shifts over time have a minimal effect on my results because I rank firms into quintiles based on their relative values at a given point in time.

Table 1, Panel C reports both the use and direction of nonfinancial measures by the number of observations and firms over my test period. From 2000 to 2012, I observe a monotonic increase in both the number of firms reporting the use and the direction of nonfinancial measures. Specifically, I find a noticeable increase post 2006 corresponding with The Securities and Exchange Commission adopting amendments to the disclosure requirements for executive and director compensation, effective November 2006.

## Empirical Models

First, I rank firms based on the consensus analyst recommendation. I/B/E/S codes recommendations into five ordered categories: strong buy = 1; buy = 2; hold = 3; sell = 4; and strong sell = 5. For analyses using recommendations, I reverse this coding (i.e., strong buy = 5; strong sell = 1) to allow for a more intuitive interpretation of my results. Each month, I use the

I/B/E/S consensus recommendation.[4] I then use ordered logistic regression analysis to provide a multivariate test of the relation between analyst investment signals and a set of 11 financial predictor variables. In all regression analyses, I assess statistical significance using test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month (Petersen 2009; Gow, Ormazabal and Taylor 2010).

*Dependent Variables*

To capture a more complete picture of factors associated with analysts' investment decisions, I study both analyst recommendations and recommendation revisions. I measure analyst recommendations (*Rec*) as the consensus analyst recommendation as of the last month in each calendar quarter, consistent with prior research.[5] I include recommendation revisions, given that prior research finds that recommendation revisions might be better indicators of future stock price performance than recommendation levels (Womack 1996; Jegadeesh, Kim, Krische and Lee 2004; Barber, Lehavy, McNichols and Trueman 2010). I calculate recommendation revisions (*ChgRec*) as the change in recommendation levels from calendar quarter $t-1$ to quarter t (i.e., consecutive quarters). An increase (decrease) in the consensus recommendation will indicate an upgrade (downgrade) in the stock relative to the previous calendar quarter $t-1$.[6]

*Independent Variables*

For my measure of financial performance, I select 11 financial variables demonstrated to be

[4] Thompson Financial claims that recommendations not updated for 180 days are excluded from the I/B/E/S consensus recommendation (see Thompson Financial 2009,11). In addition, I/B/E/S calculates the consensus recommendation on the Thursday before the third Friday of every month (ranging from the 14th to the 20th day of the month). The requirement of utilizing the consensus recommendation serves two purposes. First, short interest data are made publicly available mid-month and therefore, both signals—recommendations and short interest— are obtained at approximately the same time during the month. Second, it ensures that investors are given ample time to process and impound in price whatever new information is contained in both signals.

[5] Performing these analyses using quarterly data is intuitive given that the majority of the predictor variables (seven of the 11) change on a quarterly basis as financial information is disclosed.

[6] Ljungqvist, Malloy and Marston (2009) provide evidence that the I/B/E/S recommendations database contains systematic errors in the pre-2007 files that is likely to overstate the investment value of analysts' recommendations. This study re-examines the investment value of analysts' recommendations using the cleaned 2007 database.

predictive of returns in prior literature. I group the predictor variables into one of four classifications based on the nature of the variable (see the Appendix for details on the calculation of each variable). The first group, labeled *Accounting*, consists of earnings surprise (*SUE*), total accruals (*TACCR*), and capital expenditures (*CAPEX*). The Valuation group consists of the market-value-of-equity (*MVE*), earnings-to-price ratio (*EP*), book-to-market ratio (*BTM*), and the average daily stock turnover (*TURN*). The Growth group consists of realized sales growth (*SG*) and forecasted long-term growth (*LTG*). The fourth group, Momentum, consists of earnings forecast revision (*FREV*) and price momentum (*MOM*). These variables have been shown in prior research to be associated with future returns (see the Appendix for specific citations). Thus, I expect that sophisticated capital market participants, such as analysts and short sellers, would use information embedded in these variables when establishing their positions.

In addition, I construct a variable to measure the favorability of a firm's nonfinancial performance measures in CEO compensation. Following Ittner and Larcker (1997), I conduct a keyword search of annual proxy statements, found on the EDGAR on-line database, using terms such as "non-financial or nonfinancial," "customer satisfaction," "employee satisfaction or employee morale or employee motivation," "quality," "process improvement," "re-engineering or reengineering," "new product development," "diversity," "market share," "productivity or efficiency," "safety," "innovation," "operational measure or operational performance," and "strategic objectives."[7] Next I read the compensation committee report to confirm that the keyword(s) are used in the appropriate context. Following Said, HassabElnaby and Wier (2003),

[7] The SEC requires firms to disclose the principles underlying their executive compensation plans and performance criteria used in determining compensation. Therefore, I used the keywords mentioned above to search for firms that used the nonfinancial measure(s) in determining compensation. I classify firms that use only financial measures in their bonus plans, as well as firms that use none of the keywords in their proxy statements, as not using nonfinancial measures (*NFM* = 0; see the Appendix for examples). The remaining firms' proxies include one or more of the keywords, and I therefore classify them as using nonfinancial measures (*NFM* = 1).

I create a dummy variable (*NFM*) to capture the firm's reliance on nonfinancial measures in its bonus plans. *NFM* takes on the value of 1 if the firm uses nonfinancial measures, and 0 otherwise.[8]

In addition to identifying firm reliance on *NFM,* I also categorize the specific type of *NFM* used through its identification in the keyword search. I identify 15 categories and create dummy variables (*measure1* to *measure15*) to capture the use of the following NFM in the executive compensation package: customer satisfaction, employee satisfaction, quality, reengineering, new product development, diversity, market share, productivity, efficiency, safety, innovation, operational measures, operational performance, strategic initiatives and other, respectively (e.g. *measure3* takes on the value of 1 if the firm uses quality as a NFM measure, and 0 otherwise).

Next I search the compensation committee report for evidence of the direction of the nonfinancial performance measure. I create a dummy variable (*UNFAV*) to capture the aggregate direction of the firm's nonfinancial performance. *UNFAV* takes on the value of 1 if the firm both utilizes nonfinancial performance measures and the executive fails to meet the performance goal, and 0 if the goal is met.[9] Prior literature has shown a positive association between firms that utilize a combination of financial and nonfinancial performance metrics in CEO compensation and future returns (Said et al. 2003).

**Predictive Information Use by Analyst**

H1a and H1b predict the main effects that financial performance and the presence of nonfinancial performance are positively associated with analyst recommendations, respectively. I use Model (*1*) and Model (*2*) to examine these hypotheses. Year and industry effects are

[8] These firms are further identified into two subgroups. The first subgroup consists of firms using nonfinancial performance measures with specific weights. The second subgroup consists of firms using nonfinancial performance measures without specific weights.

[9] See the Appendix for an example

controlled in the model, and standard errors are clustered at the firm level and calendar month.

$$Rec(ChgRec) = \beta_0 + \beta_1 SUE + \beta_2 TACCR + \beta_3 CAPEX + \beta_4 MVE + \beta_5 EP + \beta_6 BTM + \beta_7 TURN + \beta_8 SG + \beta_9 LTG + \beta_{10} FREV + \beta_{11} MOM + YEAR\ INDICATORS + INDUSTRY\ INDICATORS + e_t \qquad (1)$$

$$Rec(ChgRec) = \beta_0 + \beta_1 NFM + \beta_2 SUE + \beta_3 TACCR + \beta_4 CAPEX + \beta_5 MVE + \beta_6 EP + \beta_7 BTM + \beta_8 TURN + \beta_9 SG + \beta_{10} LTG + \beta_{11} FREV + \beta_{12} MOM + YEAR\ INDICATORS + INDUSTRY\ INDICATORS + e_t \qquad (2)$$

Where

*Rec* = consensus analyst recommendation in the last month of the calendar quarter, where 5 = strong buy, 4 = buy, 3 = hold, 2 = sell, and 1 = strong sell;

*ChgRec* = change in the consensus analyst recommendation from the previous quarter;

*NFM* = 1 if a firm utilizes nonfinancial performance measures, and 0 otherwise;

*SUE* = seasonally adjusted earnings change scaled by price for fiscal quarter *q*;

*TACCR* = total accruals scaled by average assets measured at the end of fiscal quarter *q*;

*CAPEX* = rolling sum of the preceding four quarters of capital expenditures ending at fiscal quarter *q* divided by total assets;

*MVE* = market value of equity at the end of fiscal quarter *q*;

*EP* = ratio of the rolling sum of earnings over the preceding four quarters to price at the end of fiscal quarter *q*;

*BTM* = ratio of book value of equity to market value of equity as of the end of fiscal quarter *q*;

*TURN* = average daily volume per share over the preceding six months;

*SG* = rolling sum of sales growth over the preceding four fiscal quarters;

*LTG* = consensus long-term earnings growth forecast at the end of calendar quarter *t*;

*FREV* = rolling sum of the preceding six-month earnings forecast revisions scaled by price; and

*MOM* = price momentum, measured as the six-month raw return ending one month prior to the end of the fiscal quarter *q*.

The dependent variables, *Rec* and *ChgRec*, are predicted to be positively associated with the proxy for financial performance. All variable definitions are shown in Appendix.

As indicated in prior literature (Drake et al. 2011; Jegadeesh et al. 2004), my financial variables of interest have been demonstrated to predict returns.[10] I have summarized below, but the Appendix presents more detailed information on how each variable is computed. I also winsorize each of the control variables at the 1 and 99 percentiles to control for outliers. Per prior literature, I group my financial variables into one of four classifications based on the nature of the variable.

The first group, *Accounting*, will consists of total accruals (*TACCR*) and capital expenditures (*CAPEX*). *TACCR* provides a measure of the quality of earnings, and could signal earnings manipulation. For example, if firms excessively capitalize overheads into inventories, or if they fail to write off inventories in a timely manner, then the inventory component of accruals will rise. Such tactics lead to positive accruals. Sloan (1996) finds that firms with low accruals (more negative *TACCR*) earn higher future returns than firms with high accruals. He argues that the accrual-component of earnings is less persistent, and that the market does not take this effect into account in a timely fashion.

However, Chan, Chan, Jegadeesh and Lakonishok (2001) point out that firms with large sales growth also experience large contemporaneous increases in accounts receivables and

[10] See the Appendix for the corresponding citations

inventory, mainly to support the increased levels of sales. In fact, Chan et al. (2001) find that the decile of firms with the largest accruals experience sales growth of 22% per year over the prior three-year period compared to seven percent per year sales growth for the decile of low accrual firms. They also find large earnings growth for high accrual firms. Therefore, although high accruals may be symptoms of managerial manipulation in some instances, they are also associated with strong past operating performance.

Beneish, Lee, and Tarpley (2001) show that growth firms with high capital expenditure (*CAPEX*) also tend to earn lower subsequent returns. They argue that high *CAPEX* firms are growth firms that tend to overextend themselves. Again, if analysts pay attention to these results in formulating their stock picks, lower *TACCR* and lower *CAPEX* firms should receive more favorable recommendations.

The second group, *Valuation*, will consist of the market-value-of-equity (*MVE*), earnings-to-price ratio (*EP*), book-to-market ratio (*BTM*), and the average daily stock turnover (*TURN*). Banz (1981) and Reinganum (1981), among others, show that small firms have generally earned higher returns than large firms. While opinions differ on the robustness of the result and the interpretation of this variable, I will include a control for firm size. Specifically, I will compute *MVE* as the natural log of a firm's market capitalization at the end of its most recent fiscal quarter.

Both the earnings-to-price (*EP*) and book-to-market (*BTM*) ratio are widely used in valued-based investment strategies. Starting with Basu (1977), several academic studies show that high *EP* firms subsequently outperform low *EP* firms. Similarly, Fama and French (1992), among others, show that high *BTM* firms subsequently earn higher returns than low *BTM* firms. Academic opinions differ on whether these higher returns represent contrarian profits or a fair reward for risk. In either case, if analysts pay attention to the predictive ability of these multiples, I would expect high *EP* (and high *BTM*) firms to receive more favorable recommendations.

*TURN* is a measure of the average daily volume turnover ratio. Lee and Swaminathan (2000) show that high (low) volume stocks exhibit glamour (value) characteristics, and earn lower (higher) returns in subsequent months. They argue that *TURN* is a contrarian signal, and that high (low) turnover stocks are overvalued (undervalued) by investors.

The third group, *Growth*, will consist of realized sales growth (*SG*) and forecasted long-term growth (*LTG*). *LTG* (the mean analyst forecast of expected long-term growth in earnings) and *SG* (the rate of growth in sales over the past year). Lakonishok, Shleifer, and Vishny (1994) show that firms with high past growth in sales earn lower subsequent returns. They argue that high growth firms are glamour stocks that are overvalued by the market. In the same spirit, La Porta (1996) shows that firms with high forecasted earnings growth (high *LTG* firms) also earn lower subsequent returns. If analysts rely on these results, low *SG* (and low *LTG*) firms should receive more favorable recommendations.

The fourth group, *Momentum*, will consist of earnings forecast revision (*FREV*) and price momentum (*MOM*). These variables have been shown in prior research to be positively associated with future returns and I would expect high FREV and MOM firms to receive more favorable recommendations (see the Appendix for specific citations).

**Interaction Effect**

H1c predicts an interaction effect between financial performance and the direction (favorability) of the nonfinancial measure on both analyst recommendations and revisions. Specifically, when nonfinancial performance is unfavorable, the association between financial performance and analyst recommendations is weaker than when nonfinancial performance is favorable. I use Model (*3*) to examine this hypothesis. Again, year and industry effects are controlled in the model, and standard errors are clustered at the firm level and calendar month.

$$
\begin{aligned}
Rec(ChgRec) = {} & \beta_0 + \beta_1 NFM + \beta_2 UNFAV + \beta_3 SUE + \beta_4 TACCR + \beta_5 CAPEX + \beta_6 MVE \\
& + \beta_7 EP + \beta_8 BTM + \beta_9 TURN + \beta_{10} SG + \beta_{11} LTG + \beta_{12} FREV + \beta_{13} MOM \\
& + YEAR\ INDICATORS + INDUSTRY\ INDICATORS \\
& + e_t \qquad (3)
\end{aligned}
$$

where

*NFM* = 1 if a firm BOTH utilizes nonfinancial performance measures and has a measure that meets or exceeds the predetermined performance goal (favorable direction), and 0 otherwise;

*UNFAV* = 1 if a firm BOTH utilizes nonfinancial performance measures and has a measure that does not meet the predetermined performance goal (unfavorable direction), and 0 otherwise.

## RESULTS

In this section, I first examine whether analyst recommendations incorporate fundamental financial information and the presence of nonfinancial information in the manner shown by prior research to be predictive of future returns. Next, I examine whether analyst recommendations incorporate the direction (favorability) of nonfinancial information. Finally, I examine the significance of the interaction between financial information and the direction of nonfinancial information on analyst recommendations.

### Univariate Evidence

Table 2 presents mean values for each of the 11 predictive variables by quintile for recommendation levels and recommendation changes. In Panel A, as I move down each column from the worst to the best recommendations, I find a monotonic (or near monotonic) increase for eight of the 11 variables. The increase for *SUE*, *EP*, *FREV*, and *MOM* is consistent with analyst recommendations properly incorporating the relation of these measures with future returns. In contrast, the increase for *TACCR*, *CAPEX*, *SG*, and *LTG* indicate that analysts misuse this information, which could cause more favorable recommendations to foreshadow lower investment returns. The overall pattern of information use indicates that analysts tend to issue more favorable recommendations for glamour stocks, even though prior studies show that these stocks earn lower subsequent returns (Lakonishok et al. 1994; La Porta 1996; Sloan 1996; Beneish et al. 2001).

[insert Table 2]

Examining changes in recommendations, Panel B shows a clear pattern for only two variables; but in each case, the change is consistent with the relation of the information with future returns established in prior research. Specifically, as I move down the columns from downgrades to upgrades, I observe a monotonic increase for earnings forecast revisions (*FREV*) and stock price momentum (*MOM*). While prior research has generally found that recommendation revisions are better predictors of future returns than are recommendation levels, this analysis indicates that recommendation revisions fail to incorporate nine of the 11 items of predictive information. These results for recommendation levels and changes are like the results documented in prior research (Drake et al. 2011; Jegadeesh et al. 2004)

### Multivariate Evidence

First, I use ordered logistical regression analysis to provide a multivariate test of the relation between analyst investment signals and the 11 financial variables (*Model 1*). In all regression analyses, I assess statistical significance using test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month (Petersen 2009; Gow et al. 2010). Table 3, Panel A reports results using analyst recommendations and recommendation revision quintiles as the dependent variable, with quintiles coded from 1 to 5.[11]

For recommendation levels, I find that analysts correctly incorporate the implications for future returns of only one of the Accounting variables: unexpected earnings (*SUE*). Analysts do

[11] Note that quintiles are of approximate equal size (after adjusting for ties and including all recommendation revisions of zero in the middle quintile). Due to the low frequency of strong sell and sell recommendations issued by analysts, the most unfavorable recommendation quintile contains some "hold" recommendations.

not consider total accruals (*TACCR*) or capital expenditures (*CAPEX*), despite evidence that increases in those accounting measures are associated with lower future returns (Sloan 1996). Examining the Valuation measures, analysts correctly favor firms with a higher earnings-to-price ratio (*EP*). However, they also favor larger firms (*LNMVE*) firms with a low book-to-market ratio (BTM) and high growth (*LTG*), despite evidence that stock prices of such firms underperform the market. Examining the Momentum variables, analysts correctly favor firms with high earnings momentum (*FREV*) but do not consider stock price momentum (*MOM*) despite increases in this measure being associated with future returns.

The results for revisions in analysts' recommendations are reported on the right side of Table 3, Panel A. Examining the Accounting variables, I find that only (*CAPEX*) is statistically significant with the expected sign. Neither *SUE* nor *TACCR* are statistically significant. For the Valuation and Growth variables, the evidence is mixed: TURN is statistically significant in the expected direction, but BTM and LNMVE are statistically significant in the unexpected direction. *EP* is not statistically significant. The coefficient on *SG* is also significant in the unexpected direction. For the Momentum variables, I find that both *MOM* and *FREV* are statistically significant in the expected direction.

[insert Table 3]

Considering the types of information used by analysts in both their recommendations and recommendation revisions, analysts' correctly favor stocks with positive earnings momentum (*FREV*). They incorrectly favor stocks with high forecasted growth (*LTG*) and low book-to-market value (BTM). Thus, financial analysts view higher past and future growth as positive features in recommending stocks, despite research that shows the opposite relation (Lakonishok et al. 1994; La Porta 1996; Sloan 1996). In addition, analysts also tend to issue more favorable recommendations for firms with low book-to-market ratios, even though prior research shows a positive association with subsequent returns (Fama and French 1992). This evidence indicates that sell-side analysts tend to favorably recommend “glamour stocks.” Prior research (Drake et al. 2011; Jegadeesh et al. 2004) reached the same conclusion based on analyses of earlier time periods.

*Presence of Nonfinancial Measures*

I next use ordered logistical regression analysis to provide a multivariate test of the relation between analyst investment signals and the presence of nonfinancial measures (*Model 2*). Table 3, Panel B reports results using analyst recommendations and recommendation revision quintiles as the dependent variable, with quintiles coded from 1 to 5. Although the signs are in the predicted direction, I fail to find support for H1b that analysts incorporate the presence of *NFM* alone into the implications for future returns for either recommendation levels or revisions. *NFM* was not statistically significant. However, I find similar results for all 11 financial variables as detailed in the analysis in Panel A.

*Direction of Nonfinancial Measures*

I next use ordered logistical regression analysis to provide a multivariate test of the relation between analyst investment signals and the direction (favorability) of nonfinancial measures (*Model 3*). Table 3, Panel C reports results using analyst recommendations and recommendation revision quintiles as the dependent variable, with quintiles coded from 1 to 5. For recommendation levels, I find support for analysts incorporating the direction of *NFM* into their implications for future returns. The *NFM* coefficient is positive and significant, while the

*UNFAV* coefficient is negative and significant. Although the signs are in the predicted direction, I fail to find significance for either *NFM* or *UNFAV* for recommendation revisions. Again, I find similar results from all 11 financial variables for both levels and revisions.

In Table 4, I report the average marginal effects for all coefficients in *Model 3* for both dependent variables (levels and revisions). I choose to report these results as marginal effects as opposed to odds ratios for ease of interpretation. Marginal effects are interpreted as the change in probability of being in a quintile for a one unit increase in the reported variable (e.g. *SUE*, *CAPEX*, etc.) For the factor variables (i.e. *NFM*, *UNFAV*) marginal effects represent the discrete change from the base level (0,1).

[insert Table 4]

*Interaction Effect*

Finally, I use the predicted probabilities from my ordered logistical regression analysis (*Model 3*) to provide a test of the relation between analyst investment signals and the interaction between nonfinancial direction (favorability) and the 11 financial variables. Table 5, reports the predicted probabilities of a firm's inclusion in 1 of 5 quintiles (*QRec* and *QChgRec*) based on the following interactions between all 11 financial variables (*FV*) and unfavorable nonfinancial direction (*UNFAV*):

Scenario (1): both Group 1 and 2; *UNFAV*=0 and *FV* in the 75th percentile

Scenario (2): Group 1 *UNFAV*=1 and *FV* in the 75th percentile; Group 2 *UNFAV*=0 and *FV* in the 75th percentile

Scenario (3): Group 1 *UNFAV*=0 and *FV* in the 75th percentile; Group 2 *UNFAV*=0 and *FV* in the 50th percentile

Scenario (4): Group 1 *UNFAV*=1 and *FV* in the 75th percentile; Group 2 *UNFAV*=0 and

*FV* in the 50th percentile

[insert Table 5]

For Panel A, scenario (1) is the base case and assumes that both Group 1 and Group 2 are in the 75$^{th}$ percentile in all financial categories and neither group has unfavorable nonfinancial measure direction, which results in a 28 percent chance of having a consensus analyst recommendation that place both groups in the highest quintile (5).

In scenario (2), I isolate the effect of unfavorable nonfinancial direction by holding financial performance constant (both groups at the 75$^{th}$ percentile) and varying the direction of nonfinancial performance (*UNFAV*=1, Group 1 and remains 0 for Group 2). Group 1 now has an approximate 22 percent chance of being included in the highest quintile, while Group 2 remains at 28 percent, unchanged from scenario (1). In both scenarios, financial data was positive (above average) and held constant, while nonfinancial direction was changed from favorable to unfavorable for Group 1 between scenario 1 and 2. As predicted in H1c, the negative (unfavorable) *NFM* direction attenuates the positive (above average) financial information for analyst recommendations that fall within this quintile as demonstrated by the approximate six percentage (statistically significant) difference in predicted probabilities between Group 1 and 2 in scenario (2).

Additionally, scenario (3) highlights the findings from H1a that financial information has a positive association with analyst recommendation. In this case, neither Group 1 nor 2 has unfavorable nonfinancial measures (*UNFAV*=0); however, I vary the financial information to be in the 75$^{th}$ and 50$^{th}$ percentile, respectively. As expected, Group 1 (with above average financial data) has a 28 percent chance, opposed to a 21 percent chance for Group 2 (with average financial data), of being in the highest quintile. The difference is statistically significant. Again, this highlights the strength of financial data in the recommendation formation process.

In scenario (4), I examine the strength of nonfinancial direction's ability to attenuate financial information. In this case, I employ the same financial conditions for both Group1 and Group 2 as in scenario (3) (75$^{th}$ percentile and 50$^{th}$ percentile, respectively), but vary the nonfinancial measures so that Group 1 (with above average financial data) has an unfavorable nonfinancial measure, while Group 2 (with average financial data) has a favorable nonfinancial measure. As predicted, Group 1 has the better financial performance (75$^{th}$ percentile) and better chance (22 percent) of being in the highest quintile compared to Group 2 (50$^{th}$ percentile and 21 percent); however, the unfavorable nonfinancial direction for Group 1 attenuates its above average financial data. The difference between the probabilities of both Group 1 and 2 being included in the highest quintile is no longer statistically significant. My results follow the same pattern for each scenario in quintiles 4 and 5.

For quintiles 3 and below, having unfavorable measures, both financial and nonfinancial, increase, and as such, the data presents a different pattern. In other words, less favorable outcomes increase the probability of being in the lower quintiles. For scenario (2) of Table 5, Group 1 *(UNFAV*=1, 75th percentile financial) has a 24 percent probability of being in quintile 3, while Group 2 (*UNFAV*=0, 75th percentile financial) has 23 percent probability of being in the same quintile. This represents the exact opposite pattern experienced for the same scenario in quintiles 4 and 5. However, the results are consistent with my predictions and prior theory.

## ADDITIONAL ANALYSIS

As a supplementary analysis, I also investigate the context within which short sellers make decisions and then compare those results with that of analysts. Short sellers are regarded as particularly sophisticated investors under financial economic theory.[12] Like analysts, short sellers invest considerable time and resources in analyzing companies, but they face potentially different incentives. Unlike analysts who may be biased by the economic incentives faced by their sell-side brokerage firms, short sellers place their own capital at risk and have strong incentives to fully use all available predictive information (i.e. nonfinancial information).

I first examine whether short sellers incorporate fundamental financial information (*Model 4*) and the presence of nonfinancial information (*Model 5*) in the manner shown by prior research to be predictive of future returns. Next, I examine whether short sellers incorporate the direction (favorability) of nonfinancial information (*Model 6*). Finally, I examine the significance of the interaction between financial information and the direction of nonfinancial information on short sellers.

[12] Diamond and Verrecchia (1987) argue that only informed traders with strong beliefs that stock prices will fall in the near-term will choose to sell stock short. Their reasoning is based on the notion that the high costs of short selling drives out uninformed traders, so that open short positions reflect trades by more informed investors. Boehmer, Jones and Zhang (2008, 491) comment that short sellers "occupy an exalted place in the pantheon of investors as rational, informed market participants who act to keep prices in line."

$$SIratio = \beta_0 + \beta_1 SUE + \beta_2 TACCR + \beta_3 CAPEX + \beta_4 MVE + \beta_5 EP + \beta_6 BTM + \beta_7 TURN + \beta_8 SG + \beta_9 LTG + \beta_{10} FREV + \beta_{11} MOM + YEAR\ INDICATORS + INDUSTRY\ INDICATORS + e_t \quad (4)$$

$$SIratio = \beta_0 + \beta_1 NFM + \beta_2 SUE + \beta_3 TACCR + \beta_4 CAPEX + \beta_5 MVE + \beta_6 EP + \beta_7 BTM + \beta_8 TURN + \beta_9 SG + \beta_{10} LTG + \beta_{11} FREV + \beta_{12} MOM + YEAR\ INDICATORS + INDUSTRY\ INDICATORS + e_t \quad (5)$$

Where

*SIratio* = number of shares sold short as reported for the last month of the calendar quarter divided by the number of shares outstanding as of the same date;

*NFM* = 1 if a firm utilizes nonfinancial performance measures, and 0 otherwise;

And other variables are defined as in Model (*1*).

$$SIratio = \beta_0 + \beta_1 NFM + \beta_2 UNFAV + \beta_3 SUE + \beta_4 TACCR + \beta_5 CAPEX + \beta_6 MVE + \beta_7 EP + \beta_8 BTM + \beta_9 TURN + \beta_{10} SG + \beta_{11} LTG + \beta_{12} FREV + \beta_{13} MOM + YEAR\ INDICATORS + INDUSTRY\ INDICATORS + e_t \quad (6)$$

Where

*SIratio* = number of shares sold short as reported for the last month of the calendar quarter divided by the number of shares outstanding as of the same date;

*NFM* = 1 if a firm BOTH utilizes nonfinancial performance measures and has a measure that meets or exceeds the predetermined performance goal (favorable direction), and 0 otherwise;

*UNFAV* = 1 if a firm BOTH utilizes nonfinancial performance measures and has a measure that does not meet the predetermined performance goal (unfavorable direction), and 0 otherwise;

And other variables are defined as in Model (*1*).

**Multivariate Evidence**

Table 6, Panel A reports results from a model using short interest quintiles as the dependent variable (*Model 4*). I find that 6 of the 11 financial variables are statistically significant with coefficient signs in the expected direction.[13] Additionally, I note that the explanatory power of this model (Panel A, pseudo R2 = 17.75 percent) is more than double that for the similar model using recommendation levels (Table 3, Panel A, pseudo R2 of 7.3 percent) and more than triple that for the model using recommendation revisions (Table 3, Panel A, pseudo R2 of .01 percent).[14] Thus, I find that short interest is explained better by the predictive information in fundamental financial metrics than is analyst recommendation levels or revisions. My evidence is consistent with other studies that examine the association between short interest and indicators of future returns (Dechow, Hutton and Sloan 2001; Cao, Dhaliwal, Kolasinski and Reed 2007; Seybert and Wang 2009).

[insert Table 6]

As with analysts, I next use ordered logistical regression analysis to provide a multivariate

[13] Note that the explanatory variables have the opposite predicted sign in the short interest model (compared to the recommendation models).

[14] Since the dependent variables differ across models, it is not possible to test for differences in explanatory power. However, given that I have standardized the dependent variables by ranking them into quintiles, their variation is similar. Specifically, the standard deviations of the quintile ranking of analyst levels, analyst changes, and short interest are 1.44, 1.41, and 1.41, respectively. Thus, I believe a comparison of pseudo R2s is informative.

test of the relation between short interest and the presence of nonfinancial measures (*Model 5*). Table 6, Panel B reports results using short interest quintiles as the dependent variable, with quintiles coded from 1 to 5. Although the sign is in the predicted direction, I fail to find support for short sellers incorporating the presence of *NFM* alone into the implications of their short positions. *NFM* was not statistically significant. However, I find similar results for the financial variables as detailed in the analysis in Panel A.

I next use ordered logistical regression analysis to provide a multivariate test of the relation between short interest and the direction (favorability) of nonfinancial measures (*Model 6*). Table 6, Panel C reports results using short interest quintiles as the dependent variable, with quintiles coded from 1 to 5. I find support for short sellers incorporating the direction of *NFM* into the implications of their short positions. The *NFM* coefficient is negative and significant, while the *UNFAV* coefficient is positive and significant. I find similar results from all the financial variables as in previous models. Like Panel A, I note the explanatory power of this model (Table 6, Panel C, pseudo R2 = 17.81 percent) is more than double that for the similar model using recommendation levels (Table 3, Panel C, pseudo R2 of 7.4 percent) and more than triple that for the model using recommendation revisions (Table 3, Panel C, pseudo R2 of .01 percent). Thus, I find that short interest is explained better by the predictive information in nonfinancial measure direction than is analyst recommendation levels or changes.

In Table 7, I report the average marginal effects for all coefficients in *Model 6* for short interest. I choose to report these results as marginal effects as opposed to odds ratios for ease of interpretation. Marginal effects are interpreted as the change in probability of being in a quintile for a one unit increase in the reported variable (e.g. *SUE*, *CAPEX*, etc.) For the factor variables (i.e. *NFM*, *UNFAV*) marginal effects represent the discrete change from the base level (0,1).

[insert Table 7]

Finally, I use the predicted probabilities from my ordered logistical regression analysis (*Model 6*) to provide a test of the relation between short interest and the interaction between nonfinancial direction (favorability) and the 11 financial variables. Table 8, reports the predicted probabilities of a firm's inclusion in 1 of 5 quintiles (*QSIratio*) based on the following interactions between all 11 financial variables (*FV*) and unfavorable nonfinancial direction (*UNFAV*):

Scenario (1): both Group 1 and 2; *UNFAV*=0 and *FV* in the 75th percentile

Scenario (2): Group 1 *UNFAV*=1 and *FV* in the 75th percentile; Group 2 *UNFAV*=0 and *FV* in the 75th percentile

Scenario (3): Group 1 *UNFAV*=0 and *FV* in the 75th percentile; Group 2 *UNFAV*=0 and *FV* in the 50th percentile

Scenario (4): Group 1 *UNFAV*=1 and *FV* in the 75th percentile; Group 2 *UNFAV*=0 and *FV* in the 50th percentile

[insert Table 8]

In scenario (1) both Group 1 and 2 have an 11 percent probability of having short interest that place them in the highest quintile (5). In scenario (2), Group 1 has an approximate probability of 13 percent to be included in the highest quintile, while the probability of Group 2 remains unchanged. In both scenarios, financial data was positive and held constant, while nonfinancial direction was changed from favorable to unfavorable for Group 1 between scenario (1) and (2).

As predicted, *NFM* direction attenuates financial information for short interest that fall within this quintile as demonstrated by the approximate two percentage difference, in predicted probabilities between Group 1 and 2 in scenario (2). The unfavorable nonfinancial direction has increased the chance Group 1 will be included in the highest short interest quintile despite having "above average" financial performance. However, unlike in the analyst analysis, the difference between the probabilities of Group 1 and 2 is not statistically significant. I find a consistent pattern throughout quintiles.

## ROBUSTNESS TESTS

In this section, I report the results of my robustness tests (all untabulated). I begin by examining the sensitivity of the results to using an interaction term between industry indicators and year indicators to allow for different time effects for each industry. I find the results qualitatively the same as those reported in my initial regressions.

Next, I use an alternative short interest variable. In my additional analyses, I used the short interest ratio (open short interest divided by shares outstanding). As an alternative deflator, I scale open interest by the previous month's trading volume and label this *SIVOL*. I find that *SIVOL* is highly correlated with the short interest ratio. When I regress the quintile assignment of *SIVOL* on the financial and nonfinancial variables, I again find results qualitatively the same as those reported using the short interest ratio.

## CONCLUSION

I contribute new findings on how sell-side analysts incorporate publicly available information signals, both financial and nonfinancial, in their implications of future returns, and contrast how short sellers incorporate the same information. By so doing, I expand upon the results of Drake et al. (2011) and other studies that examine information used by analysts and short sellers.[15] Consistent with prior research, I first find analysts and short sellers use publicly available information differently. Analysts over-recommend stocks with high growth and low book-to-market ratios, even though prior research shows these characteristics are negatively related to future returns. Second, I find that neither analysts nor short sellers incorporate the presence of *NFM* alone in their implications of future returns. Third, I find both analysts and short sellers incorporate the direction (favorability) of *NFM* in their implications of future returns. Last, I find unfavorable *NFM* attenuates positive financial information for analyst recommendations; however, I find no statistically significant support for short interest.

My study contributes to the stream of academic literature on nonfinancial performance measures. A key assumption, underlying both the predictive and incremental value of nonfinancial measures, is the inclusion of nonfinancial measures will more closely align effort, emphasized by said measures, which in turn results in improvements in performance. However, prior research has focused solely on the inclusion of nonfinancial measures and not the alignment

[15] Dechow et al. 2001; Cao et al. 2007; Seybert and Wang 2009.

between the nonfinancial measure and the effort, it seeks to emphasize. Effort which is expressed by the direction (i.e. favorability) of the measure. I show that analyst and short sellers properly incorporate the direction of *NFM* in both recommendations and short positions, respectively. In addition, I show unfavorable nonfinancial measures attenuate positive financial information in analysts' recommendations.

My study is timely as there has been a significant increase in the disclosure of nonfinancial information over my analysis period. Specifically, reporting requirements in executive compensation have resulted in an increase in the use of compensation consultants by boards of directors in structuring executive compensation packages. An important implication of my study is that analysts and other interested parties are taking note of the direction (favorability) of nonfinancial data and incorporating this ancillary information in recommendation and investment decisions. Therefore, it is incumbent on firms to clearly define nonfinancial measures and the effort they seek to emphasize, especially as they pertain to executive compensation.

## REFERENCES


Ackert, L. F., Church, B. K., and Shehata, M. 1996. What affects individuals' decisions to acquire forecasted information? *Contemporary Accounting Research* 13(2): 379.

Amir, E. and B. Lev. 1996. Value-relevance of non-financial information: The wireless communication industry. *Journal of Accounting and Economics* 22 (1/3): 3–30.

Anderson, E. W. 1988. Transaction costs as determinants of opportunism in integrated and independent sales forces. *Journal of Economic Behavior and Organization* 9 (3): 247–264.

Anderson, E. W., and L. C. Salisbury. 2003. The formation of market-level expectations and its covariates. *Journal of Consumer Research* 30 (1): 115–124.

Banker, R. D., and S. M. Datar. 1989. Sensitivity, precision, and linear aggregation of signals. *Journal of Accounting Research* 27 (1): 21–40.

Banker, R.D., G. Potter, and D. Srinivisan. 2000. An empirical investigation of an incentive plan that includes nonfinancial performance measures. *The Accounting Review* 75 (1): 65–92.

Banz, R. W. 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics* 9(1): 3-18.

Barber, B. M., R. Lehavy, M. McNichols, and B. Trueman. 2010. Ratings changes, ratings levels, and the predictive value of analysts' recommendations. Financial Management 39 (2): 533–553.

Barron, O. E., Kile, C. O., and O'Keefe, T. B. 1999. MD&A Quality as Measured by the SEC and Analysts' Earnings Forecasts. *Contemporary Accounting Research* 16(1): 75-109.

Basu, S. 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance* 32(3): 663-682.

Behn, B., and R. Riley. 1999. Using nonfinancial information to predict financial performance: The case of the U.S. airline industry. *Journal of Accounting, Auditing, and Finance* 14: 29–56.

Beneish, M. D., C. M. C. Lee, and R. L. Tarpley. 2001. Contextual fundamental analysis through the prediction of extreme returns. Review of Accounting Studies 6 (2–3): 165–189.

Bernard, V. L., and J. K. Thomas. 1989. Post-earnings-announcement drift: Delayed price response or risk premium? Journal of Accounting Research 27 (Supplement): 1–36.

Boehmer, E., C. M. Jones, and X. Zhang. 2008. Which shorts are informed? The Journal of Finance 63 (2): 491–527.

Bouwman, M. L., P. A. Frishkoff, and P. Frishkoff. 1987. How do financial analysts make decisions? A process model of the investment screening division. *Accounting, Organizations and Society* 12 (1): 1–29.

Breton, G., and R. J. Taffler. 2001. Accounting information and analyst stock recommendation decisions: A content analysis approach. *Accounting and Business Research* 31 (2): 91–101.

Broadbent, D. E. 1971. Decision and Stress. London, U.K.: Academic Press.

Brown, L. D. 2000. I/B/E/S Research Bibliography, Sixth Edition (Blackwell, USA).

Cairney, T. D., and Richardson, F. M. 1998. The credibility of management forecasts of annual earnings. Available at SSRN 77508.

Cao, B., D. Dhaliwal, A. C. Kolasinski, and A. V. Reed. 2007. Bears and numbers: Investigating how short sellers exploit and affect earnings-based pricing anomalies. Working paper. University of Washington.

Chan, L. K. C., N. Jegadeesh, and J. Lakonishok. 1996. Momentum strategies. The Journal of Finance 51 (5): 1681–1713.

Chan, K., Chan, L. K., Jegadeesh, N., and Lakonishok, J. 2001. Earnings quality and stock returns (No. w8308). National bureau of economic research.

Coram, P. J., T. J. Mock, and G. S. Monroe. 2011. Financial analysts' evaluation of enhanced disclosure of non-financial performance indicators. *The British Accounting Review* 43: 87–101.

Das, S. 1998. Financial analysts' earnings forecasts for loss firms. *Managerial Finance* 24 (6): 39–50.

Dechow, P. M., A. P. Hutton, L. Meulbroek, and R. G. Sloan. 2001. Short-sellers, fundamental analysis, and stock returns. Journal of Financial Economics 61 (1): 77–106.

Dempsey, S. J., J. F. Gatti, D. J. Grinell, and W. L. Cats-Baril. 1997. The use of strategic performance variables as leading indicators in financial analysts' forecasts. *The Journal of Financial Statement Analysis* 2 (4): 61–79.

Diamond, D. W., and R. E. Verrecchia. 1987. Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics 18 (2): 277–311.

Drake, M. S., Rees, L., and Swanson, E. P. 2011. Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers. *The Accounting Review* 86(1): 101-130.

Eagly, A. H., and S. Chaiken. 1975. An attribution analysis of the effect of communicator characteristics on opinion change: The case of communicator attractiveness. *Journal of Personality and Social Psychology* (July): 136–144.

Eccles, R., R. Herz, E. Keegan, and D. M. H. Phillips. 2001. The Value Reporting Revolution. New York, NY: John Wiley and Sons.

Elton, J., Gruber, M., and Grossman, S. 1986. Discrete expectational data and portfolio performance. *Journal of Finance* 41: 699–713.

Epstein, M. J., and K. J. Palepu. 1999. What financial analysts want. *Strategic Finance* 80 (10): 48–52.

Fama, E. F., and K. R. French. 1992. The cross-section expected returns on stock and bonds. *Journal of Finance* 47: 427–465.

Feltham, G. A., and J. Xie. 1994. Performance measures congruity and diversity in multi-task principal / agent relations. *The Accounting Review* 69 (July): 429–453.

Fields, T. D., Lys, T. Z., and Vincent, L. 2001. Empirical research on accounting choice. *Journal of Accounting and Economics* 31(1): 255-307.

Fiske, S., and M. Pavelchak. 1986. Category-based versus piecemeal-based affective responses: Developments in schema-triggered effect. In Handbook of Motivation and Cognition, edited by Sorrentino, R., and E. Higgins 167–203. New York, NY: Guilford Press.

Foster, G., and M. Gupta. 1997. The customer profitability implications of customer satisfaction. Working paper, Stanford University and Washington University.

Francis, J., and Soffer, L. 1997. The relative informativeness of analysts' stock recommendations and earnings forecast revisions. *Journal of Accounting Research* 35(2): 193-211.

Garcia-Meca, E., and I. Martinez. 2007. The use of intellectual capital information in investment decisions: An empirical study using analyst reports. *The International Journal of Accounting* 42 (1): 57–81.

Gigler, F. 1994. Self-enforcing voluntary disclosures. *Journal of Accounting Research*, 224-240.

Gow, I. D., G. Ormazabal, and D. Taylor. 2010. Correcting for cross-sectional and time-series dependence in accounting research. The Accounting Review 85 (2): 483–512.

HassabElnaby, H., Said, A. A., & Wier, B. 2005. The retention of nonfinancial performance measures in compensation contracts. *Journal of Management Accounting Research* 17: 23–42.

Hassell, J., R. Jennings, and D. Lasser. 1988. Management earnings forecasts: Their usefulness as a source of firm-specific information to security analysts. *Journal of Financial Research* 11 (4): 303– 319.

Hemmer, T. 1996. On the design and choice of ‘‘modern’’ management accounting measures. *Journal of Management Accounting Research*: 87–116.

Hirst, D. E., Koonce, L., and Simko, P. J. 1995. Investor reactions to financial analysts' research reports. *Journal of Accounting Research* 335-351.

Holmstrom, B. 1979. Moral hazard and observability. Bell Journal of Economics 10: 74–91.

Hutton, A., G. Miller, and D. Skinner. 2003. The role of supplementary statements with management earnings forecasts. *Journal of Accounting Research* 41: 867–890.

Ittner, C. D., and D. F. Larcker. 1997. Quality strategy, strategic control systems, and organizational performance. *Accounting, Organizations and Society* 22 (3–4): 293–314.

Ittner, C.D., and D.F. Larcker. 1998a. Are nonfinancial measures leading indicators of financial performance? An analysis of customer satisfaction. *Journal of Accounting Research* 36: 1–35.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance 48 (1): 65–91.

Jegadeesh, N., J. Kim, S. D. Krische, and C. M. C. Lee. 2004. Analyzing the analysts: When do recommendations add value? Journal of Finance 59 (3): 1083–1124.

Kahneman, D., and A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47: 263–292.

Kahneman, D., and A. Tversky. 1984. Choices, values, and frames. *American Psychologist* 39: 341–350.

Kaplan, S., and D. Norton. 1992. The balanced-scorecard: Measures that drive performance. *Harvard Business Review* (January–February): 71–79.

Lakonishok, J., A. Shleifer, and R. W. Vishny. 1994. Contrarian investment, extrapolation, and risk. The Journal of Finance 49: 1541–1578.

La Porta, R. 1996. Expectations and the cross-section of stock returns. The Journal of Finance 51: 1715– 1742.

Lee, C. M. C., and B. Swaminathan. 2000. Price momentum and trading volume. The Journal of Finance 55 (5): 2017–2070.

Lev, B., and Zarowin, P. 1999. The Boundaries of Financial Reporting and How to Extend Them (Digest Summary). *Journal of Accounting Research* 37(2): 353-385.

Liang, C. J., and Yao, M. L. 2005. The value-relevance of financial and nonfinancial information—Evidence from Taiwan's information electronics industry. *Review of Quantitative Finance and Accounting* 24(2): 135-157.

Ljungqvist, A., C. Malloy, and F. Marston. 2009. Rewriting history. The Journal of Finance 64 (4): 1935– 1960.

Low, J., and T. Siesfield. 1998. Measures that matter. *Strategy and Leadership* (March/April): 24–38.

McNichols, M. 1989. Evidence of informational asymmetries from management earnings forecasts and stock returns. *The Accounting Review* 64 (1): 1–27.

Mercer, M. 2005. The fleeting effects of disclosure forthcomingness on management's reporting credibility. *The Accounting Review* 80 (2): 723–744.

Opdyke, J. 2000. Best on the Street 2000 Analysts Survey: The winningest pros of them all. *Wall Street Journal* (July 25): 13.

Orens R., and N. Lybaert. 2007. Does the financial analysts' usage of nonfinancial information influence the analysts' forecast accuracy? Some evidence from the Belgian sell-side financial analysts. *International Journal of Accounting* 42 (3): 237–271.

Peeters, G., and J. Czapinski. 1990. Positive-negative asymmetry in evaluations: The distinction between affective and informational negativity effects. In *European Review of Social Psychology*, edited by Stroebe, W., and M. Hewstone (1, 33–60). Chichester, U.K.: Wiley.

Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22 (1): 435–480.

Reinganum, M. R. 1981. Misspecification of Capital Asset Pricing: Empirical anomalies based on earnings' yield and market values. *Journal of Financial Economics* 9: 19–46.

Said, A. A., HassabElnaby, H. R., & Wier, B. 2003. An empirical investigation of the performance consequences of nonfinancial measures. *Journal of Management Accounting Research* 15, 193–223.

Schipper, K. 1991. Analysts' forecasts. *Accounting Horizons* 5: 105–121.

Skinner, D.J. 2008. Accounting for intangibles—a critical review of policy recommendations. *Accounting and Business Research* 38 (3): 191–204.

Skowronski, J. J., and D. E. Carlston. 1989. Negativity and extremity biases in impression formation: A review of explanations. *Psychological Bulletin* 105: 131–142.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review 71 (3): 289–315.

Stark, A. 2008. Intangibles and research – an overview with a specific focus on the UK. *Accounting and Business Research* 38(3): 275–285.

Seybert, N., and S. Wang. 2009. False prophets: How analysts lead short sellers astray during periods of high investor sentiment. Working paper. The University of Texas at Austin.

Taylor, S. E. 1991. Asymmetrical effects of positive and negative events: The mobilization-minimization hypothesis. *Psychological Bulletin* 110: 67–85.

Thompson Financial. 2009. Methodology for Estimates. Available at: http://www.library.kent.edu/files/ TF_Methodology_for_Estimates_October_2009.pdf

Vanstraelen, A., M. Zarzeski, and S. Robb. 2003. Corporate nonfinancial disclosure practices and financial analyst behavior across three European countries. *Journal of International Financial Management and Accounting* 14 (3): 249–278.

Williams, P. 1996. The relation between a prior earnings forecast by management and analysts' response to a current management forecast. *The Accounting Review* 71 (1): 103–113.

Womack, K. 1996. Do brokerage analysts' recommendations have investment value? The Journal of Finance 51: 137–167.

# APPENDIX

## QUANTITATIVE (FINANCIAL) INVESTMENT SIGNALS

The last month of each calendar quarter is labeled quarter $t$. On this date, I will measure the stock recommendation and short interest variables. Relative to this date, I will label as quarter $q$ the most recent fiscal quarter for which an earnings announcement is made at least two months prior to the end of quarter $t$ and no more than four quarters prior to the end of quarter $t$.

| Variable | Description | Calculation Details | Normative correlation with subsequent returns |
|---|---|---|---|
| *SUE* | Unexpected earnings | Seasonally adjusted earnings scaled by price for fiscal quarter $q$, as calculated by: $\frac{EPS_q - EPS_{q-4}}{Price_q}$, where *EPS* = earnings per share before extraordinary items (DATA#19) divided by the split adjustment factor (DATA#17) [Compustat]; and *Price* = stock price (DATA#14) divided by the split adjustment factor (DATA#17) [Compustat]. | Positive (Bernard and Thomas 1989) |
| *TACCR* | Total accruals | Earnings before extraordinary items and discontinued operations (DATA#76) minus cash flow from operations (DATA#108– DATA#78), scaled by average assets (DATA#44) as measured at the end of fiscal quarter $q$ [Compustat]. Since Compustat reports cumulative (i.e., year-to-date) data for cash flow items, adjustments were made to arrive at total accruals for fiscal quarter $q$ (see Collins and Hribar 2000). | Negative (Sloan 1996) |
| *CAPEX* | Capital expenditures | Rolling sum of the preceding four quarters of capital expenditures ending at fiscal quarter $q$ divided by average total assets as calculated by: $\frac{\sum_{i=0}^{3} Capex_{q-i}}{(TA_q+TA_{q-4})/2}$, where *Capex* = capital expenditures (DATA#90); and *TA* = total Assets (DATA#44). | Negative (Beneish et al. 2001) |
| *MVE* | Market capitalization | Natural log of the market value of equity at the end of fiscal quarter $q$, as calculated by DATA#14 × DATA#61 [Compustat]. | Negative (Fama and French 1992) |
| *EP* | Earnings-to-price ratio | Ratio of the rolling sum of earnings over the preceding four quarters divided by price at the end of fiscal quarter $q$, as calculated by: $\sum_{i=0}^{3} \frac{EPS_{q-i}}{Price_q}$, where *EPS* = earnings per share before extraordinary items (DATA#19) divided by the split adjustment factor (DATA#17) [Compustat]; and *Price* = stock price (DATA#14) divided by the split adjustment factor (DATA#17) [Compustat]. | Positive (Fama and French 1992) |
| *BTM* | Book-to-market ratio | Ratio of the book value of equity to the market value of equity at the end of fiscal quarter $q$, as calculated by DATA#59/(DATA#14 × DATA#61) [Compustat]. | Positive (Fama and French 1992) |

*(continued on next page)*

| Variable | Description | Calculation Details | Normative correlation with subsequent returns |
|---|---|---|---|
| *TURN* | Stock turnover | Average daily volume turnover ratio measured as the exchange-specific, percentile rank of: $\sum_{i=1}^{n} \frac{Daily\ Vol./Shrout}{n}$, where *Daily Vol.* = daily stock volume [CRSP]; *Shrout* = shares outstanding [CRSP]; and $n$ = the number of trading days for the six-month period ending on the last trading day of calendar quarter $t$. | Negative (Lee and Swaminathan 2000) |
| *SG* | Sales growth | Rolling sum of the preceding four quarters of sales ending at fiscal quarter $q$ divided by the rolling sum of the preceding four quarters of sales ending on quarter $q-1$, as calculated by: $\frac{\sum_{i=0}^{3} Sales_{q-i}}{\sum_{i=0}^{3} Sales_{q-4-i}}$, where *Sales* = DATA#2 [Compustat]. | Negative (Lakonishok et al. 1994) |
| *LTG* | Long-term growth forecast | Mean, consensus long-term earnings growth forecast at the end of calendar quarter $t$ [I/B/E/S]. | Negative (Lakonishok et al. 1994; La Porta 1996) |
| *FREV* | Forecast revision | Rolling sum of the preceding six-month earnings forecast revisions to price ratios, as calculated by: $\sum_{i=0}^{5} \frac{FEPS_{m-i} - FEPS_{m-i-1}}{Price_{m-i-1}}$, where *FEPS* = mean, consensus analyst forecast for one-year-ahead (FY1) earnings-per-share [I/B/E/S]; $m$ = the last month of calendar quarter $t$; and *Price* = stock price just prior to the consensus measurement date [I/B/E/S]. | Positive (Bernard and Thomas 1989; Chan et al. 1996) |
| *MOM* | Stock momentum | Buy-and-hold raw stock return for six-month period ending one month prior to the end of quarter $t$ [CRSP]. | Positive (Jegadeesh and Titman 1993) |

## QUALITATIVE (NONFINANCIAL) INVESTMENT SIGNAL

The following illustrates a single example of the data collection effort to operationalize the construct of “favorableness” in the nonfinancial performance measure. The example utilizes an excerpt from the 2013 DEF-14A (Proxy Statement) of DTE Energy Company (Specifically the Executive Compensation Section).

For Messrs. Anderson, Meador and Peterson:

| Measures | Weight | Threshold | Target | Maximum | Result | Payout % | Weighted Average Payout % |
|---|---|---|---|---|---|---|---|
| DTE Energy Adjusted EPS | 25.0% | $ 3.60 | $ 3.80 | $ 4.00 | $ 3.94 | 152.5% | 38.1% |
| DTE Energy Adjusted Cash Flow ($ millions) | 25.0% | $ 220 | $ 400 | $ 580 | $ 937.3 | 175.0% | 43.8% |
| Customer Satisfaction Index | 5.0% | 70.0% | 71.0% | 73.0% | 72.0% | 137.5% | 6.9% |
| Customer Satisfaction Improvement Program | 7.0% | 5.0% ê | 15.0% ê | 25.0% ê | 1.0% ê | 0.0% | 0.0% |
| MPSC Customer Complaints | 5.0% | 2,743 | 2,500 | 2,250 | 2,400 | 130.0% | 6.5% |
| Safety Index | 7.0% | 1.30 | 1.10 | 1.00 | 1.24 | 47.5% | 3.3% |
| Employee Engagement - Gallup | 5.0% | 3.98 | 4.03 | 4.08 | 4.08 | 175.0% | 8.8% |
| Diversity Hiring - Minority | 2.5% | 15.3% | 17.0% | 18.7% | 26.3% | 175.0% | 4.4% |
| Diversity Hiring - Female | 2.5% | 29.3% | 32.5% | 35.8% | 43.6% | 175.0% | 4.4% |
| Utility Operating Excellence Index: | | | | | | | |
| DTE Electric Distribution System Reliability (# millions) | 4.0% | 648 | 584 | 520 | 410 | 175.0% | 7.0% |
| DTE Electric Power Plant Reliability | 4.0% | 10.4% | 9.4% | 8.9% | 6.6% | 175.0% | 7.0% |
| Nuclear Generation On-line Unit Capability | 4.0% | 93.3% | 96.2% | 97.2% | 60.7% | 0.0% | 0% |
| DTE Gas Distribution System Improvement | 4.0% | 8,000 | 5,000 | 3,500 | 4,396 | 130.2% | 5.2% |
| Total | 100% | | | | | | 135.4% |

The measures in the above table are defined below:

DTE Energy Adjusted EPS - DTE Energy net income after adjustments for certain non-operating items approved by the O&C Committee, divided by average shares outstanding, fully diluted.

DTE Energy Adjusted Cash Flow - DTE Energy net cash from operating activities adjusted by utility capital expenditures, asset sale proceeds and other items approved by the O&C Committee.

Customer Satisfaction Index - Satisfaction of six key drivers of residential customer satisfaction: (1) electric delivery, (2) gas delivery, (3) electric pricing, (4) gas pricing, (5) service reputation, and (6) corporate image using industry standard methodology developed by Market Strategies International.

Customer Satisfaction Improvement Program - The calculation for defects per million opportunities which will include defects from DTE Cares callbacks and total complaints (MPSC, corporate and web assists) measured as a reduction from 2011 rate.

MPSC Customer Complaints - Number of complaints received by the MPSC in the calendar year for all business units across DTE Energy.

*(continued on next page)*

*Data Collection (Example)*

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ob | GVKE | CONM | TIC | CIK | CUSIP | NAICS | SIC | NFM_201 | Code_2013_ | Code_2013_ | Code_2013_ | Code_2013_ | Weight_201 |
| 65 | | 3459 | CONTINENTAL CORP | CIC.3 | 0000024011 | | | | . | . | . | . | . | . |
| 66 | | 3480 | CERIDIAN CORP | CEN | 0001124887 | | | | . | . | . | . | . | . |
| 67 | | 3527 | CORESTATES FINANCIAL CORP | CFL.1 | 0000069952 | | | | . | . | . | . | . | . |
| 68 | | 3555 | COUNTRYWIDE FINANCIAL CORP | CFC.3 | 0000025191 | | | | . | . | . | . | . | . |
| 69 | | 3610 | CROSS & TRECKER CORP | CTCO. | | | | | | | | | | |
| 70 | | 3734 | DANA HOLDING CORP | DCNAQ | 0000026780 | | | | 0 | 0 | 0 | 0 | 0 | 0 |
| 71 | | 3760 | DATA GENERAL CORP | DGN. | 0000026999 | | | | . | . | . | . | . | . |
| 72 | | 3782 | CATTLESALE CO | 3DYHGQ | 0000205239 | | | | . | . | . | . | . | . |
| 73 | | 3897 | DTE ENERGY CO | DTE | 0000936340 | | | | 1 | 1 | 2 | 6 | 12 | 0.5 |
| 74 | | 3980 | DISNEY (WALT) CO | DIS | 0001001039 | | | | 1 | 13 | 0 | 0 | 0 | 0 |
| 75 | | 4016 | DOLLAR GENERAL CORP | DG.1 | 0000029534 | | | | 0 | 0 | 0 | 0 | 0 | 0 |
| 76 | | 4029 | DOMINION RESOURCES INC | D | 0000715957 | | | | 1 | 10 | 14 | 0 | 0 | 0 |
| 77 | | 4066 | OMNICOM GROUP | OMC | 0000029989 | | | | 0 | 0 | 0 | 0 | 0 | 0 |
| 78 | | 4093 | DUKE ENERGY CORP | DUK | 0001326160 | | | | 1 | 13 | 10 | 14 | 0 | 0.1 |
| 79 | | 4199 | EATON CORP PLC | ETN | 0000031277 | | | | . | . | . | . | . | . |
| 80 | | 4242 | EL PASO CORP | EP | 0001066107 | | | | . | . | . | . | . | . |
| 81 | | 4393 | TXU GAS CO | TXU2 | 0000033015 | | | | . | . | . | . | . | . |
| 82 | | 4430 | EQT CORP | EQT | 0000033213 | | | | 1 | 6 | 10 | 13 | 0 | 0 |

**Where:**

*NFM_2013*= 1 if the company uses a combination of financial and nonfinancial performance measures; 0 otherwise.

*Code_1 to _4*= Represent the type of nonfinancial measure used (i.e. 1-Customer satisfaction; 2-Empoyee satisfaction; 6-Diversity; 12-Operational measure)

*Weight_*= Represents the weight of nonfinancial performance in overall compensation (i.e. .5= 50%)

(continued on next page)

*Data Collection (Favorability)*

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ob | GVKE | CONM | TIC | CIK | CUSIP | NAICS | SIC | NFM_2013 | Code_2013_ | Code_2013_ | Code_2013_ | Code_2013_ | 2013_FAV |
| 71 | | 3760 | DATA GENERAL CORP | DGN. | 0000026999 | | | | . | . | . | . | . | . |
| 72 | | 3782 | CATTLESALE CO | 3DYHGQ | 0000205239 | | | | . | . | . | . | . | . |
| 73 | | 3897 | DTE ENERGY CO | DTE | 0000936340 | | | | 1 | 1 | 1 | 1 | 0 | 1 |

**Where:**

*NFM_2013*= 1 if the company uses a combination of financial and nonfinancial performance measures; 0 otherwise.
*Code_1 to _4*= 1 if the nonfinancial performance measure was met; 0 otherwise.
*2013_FAV*= A composite measure of Code_1 to _4 that is 1 if the nonfinancial performance is deemed favorable; 0 otherwise.

## TABLE 1

## Descriptive Statistics

**Panel A: Summary Statistics for Dependent and Explanatory Variables**

| Variable | Mean | Std. | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|
| *Rec* | 3.66 | 0.43 | 2.00 | 3.43 | 3.68 | 3.87 | 5.00 |
| *ChgRec* | −0.01 | 0.19 | −2.00 | −0.09 | 0.00 | 0.06 | 2.00 |
| *SIratio* | 3.6% | 4.1% | 0.0% | 1.5% | 2.3% | 3.8% | 46.2% |
| *NFM* | 0.60 | 0.49 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| *UNFAV* | 0.10 | 0.30 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| *SUE* | 0.040 | 3.05 | −37.72 | −0.850 | −0.070 | 0.960 | 211.92 |
| *TACCR* | 0.010 | 0.090 | −5.70 | −0.010 | 0.010 | 0.030 | 0.440 |
| *CAPEX* | 0.120 | 0.130 | 0.000 | 0.040 | 0.080 | 0.150 | 1.60 |
| *MVE* | 19,901 | 34,595 | 71 | 3,901 | 8,311 | 18,466 | 282,006 |
| *EP* | 0.030 | 0.290 | −15.81 | 0.030 | 0.050 | 0.070 | 1.00 |
| *BTM* | 0.450 | 0.420 | −5.41 | 0.220 | 0.360 | 0.590 | 13.09 |
| *TURN* | 0.090 | 0.080 | 0.000 | 0.040 | 0.060 | 0.100 | 2.63 |
| *SG* | 1.15 | 19.23 | −2.22 | 1.00 | 1.02 | 1.04 | 2957.78 |
| *LTG* | 13.11 | 7.78 | −90.20 | 9.07 | 12.00 | 15.44 | 161.80 |
| *FREV* | 0.000 | 0.060 | −3.80 | 0.000 | 0.000 | 0.010 | 1.22 |

**Panel B: Analyst Recommendations and Short Interest Values by Calendar Year**

| Year | n | Mean *Rec* | n | Mean *SIratio* |
|---|---|---|---|---|
| 2000 | 1,434 | 4.00 | 1,151 | 2.1% |
| 2001 | 1,545 | 3.89 | 1,228 | 2.6% |
| 2002 | 1,579 | 3.68 | 1,258 | 2.9% |
| 2003 | 1,647 | 3.47 | 1,554 | 3.0% |
| 2004 | 1,662 | 3.55 | 1,647 | 3.1% |
| 2005 | 1,684 | 3.57 | 1,665 | 3.1% |
| 2006 | 1,735 | 3.59 | 1,720 | 3.3% |
| 2007 | 1,745 | 3.60 | 1,720 | 3.3% |
| 2008 | 1,734 | 3.63 | 1,704 | 5.0% |
| 2009 | 1,730 | 3.60 | 1,697 | 4.3% |

*(continued on next page)*

**Panel B: Analyst Recommendations and Short Interest Values by Calendar Year**

| Year | n | Mean *Rec* | n | Mean *SIratio* |
|---|---|---|---|---|
| 2010 | 1,770 | 3.70 | 1,741 | 3.8% |
| 2011 | 1,786 | 3.71 | 1,767 | 3.7% |
| 2012 | 1,817 | 3.66 | 1,797 | 4.0% |
| 2013 | 1,666 | 3.61 | 1,204 | 3.6% |
| Full Sample | 23,534 | 3.66 | 21,853 | 3.6% |

The samples consist of 23,534 (*Rec*) and 21,853 (*SIratio*) firm-quarter observations, respectively, during the period 2000–2013. See the Appendix for a more detailed description of how each variable is calculated.

Variable Definitions:
*Rec* = consensus analyst recommendation in the last month of the calendar quarter, where 5 = strong buy, 4 = buy, 3 = hold, 2 = sell, and 1 = strong sell;
*ChgRec* = change in the consensus analyst recommendation from the previous quarter;
*SIratio* = number of shares sold short as reported for the last month of the calendar quarter divided by the number of shares outstanding as of the same date;
*NFM* = takes on the value of 1 if the firm uses nonfinancial measures, and 0 otherwise;
*UNFAV* = takes on the value of 1 if *NFM*=1 and the firm executive has NOT met pre-determined nonfinancial performance measures, and 0 otherwise;
*SUE* = seasonally adjusted earnings change scaled by price for fiscal quarter *q*;
*TACCR* = total accruals scaled by average assets measured at the end of fiscal quarter *q*;
*CAPEX* = rolling sum of the preceding four quarters of capital expenditures ending at fiscal quarter *q* divided by total assets;
*MVE* = market value of equity at the end of fiscal quarter *q*;
*EP* = ratio of the rolling sum of earnings over the preceding four quarters to price at the end of fiscal quarter *q*; *BTM* = ratio of book value of equity to market value of equity as of the end of fiscal quarter *q*;
*TURN* = average daily volume per share over the preceding six months;
*SG* = rolling sum of sales growth over the preceding four fiscal quarters;
*LTG* = consensus long-term earnings growth forecast at the end of calendar quarter *t*;
*FREV* = rolling sum of the preceding six-month earnings forecast revisions scaled by price; and
*MOM* = price momentum, measured as the six-month raw return ending one month prior to the end of the fiscal quarter *q*.

*(continued on next page)*

**Panel C: Nonfinancial and Favorability Frequency by Calendar Year**

| Year | *NFM* observations | #Firms | *UNFAV* observations | #Firms |
|---|---|---|---|---|
| 2000 | 468 | 117 | 61 | 18 |
| 2001 | 566 | 143 | 38 | 13 |
| 2002 | 590 | 149 | 85 | 22 |
| 2003 | 705 | 177 | 85 | 25 |
| 2004 | 742 | 186 | 71 | 21 |
| 2005 | 854 | 215 | 38 | 12 |
| 2006 | 940 | 235 | 56 | 18 |
| 2007 | 1,096 | 274 | 120 | 37 |
| 2008 | 1,157 | 290 | 193 | 57 |
| 2009 | 1,223 | 308 | 302 | 84 |
| 2010 | 1,340 | 335 | 262 | 76 |
| 2011 | 1,379 | 347 | 180 | 55 |
| 2012 | 1,393 | 349 | 292 | 82 |
| 2013 | 1,288 | 322 | 275 | 78 |
| Sample Totals | 13,741 | 538 | 2,058 | 538 |

The samples consist of 23,534 (*Rec*) and 21,853 (*SIratio*) firm-quarter observations, respectively, during the period 2000–2013. See the Appendix for a more detailed description of how each variable is calculated.

Variable Definitions:
*Rec* = consensus analyst recommendation in the last month of the calendar quarter, where 5 = strong buy, 4 = buy, 3 = hold, 2 = sell, and 1 = strong sell;
*ChgRec* = change in the consensus analyst recommendation from the previous quarter;
*SIratio* = number of shares sold short as reported for the last month of the calendar quarter divided by the number of shares outstanding as of the same date;
*NFM* = takes on the value of 1 if the firm uses nonfinancial measures, and 0 otherwise;
*UNFAV* = takes on the value of 1 if *NFM*=1 and the firm executive has NOT met pre-determined nonfinancial performance measures, and 0 otherwise;
*SUE* = seasonally adjusted earnings change scaled by price for fiscal quarter *q*;
*TACCR* = total accruals scaled by average assets measured at the end of fiscal quarter *q*;
*CAPEX* = rolling sum of the preceding four quarters of capital expenditures ending at fiscal quarter *q* divided by total assets;
*MVE* = market value of equity at the end of fiscal quarter *q*;
*EP* = ratio of the rolling sum of earnings over the preceding four quarters to price at the end of fiscal quarter *q*; *BTM* = ratio of book value of equity to market value of equity as of the end of fiscal quarter *q*;
*TURN* = average daily volume per share over the preceding six months;
*SG* = rolling sum of sales growth over the preceding four fiscal quarters;
*LTG* = consensus long-term earnings growth forecast at the end of calendar quarter *t*;
*FREV* = rolling sum of the preceding six-month earnings forecast revisions scaled by price; and
*MOM* = price momentum, measured as the six-month raw return ending one month prior to the end of the fiscal quarter *q*.

**TABLE 2**

**Mean Values by Quintile for 11 Variables Associated with Future returns**

**Panel A: Recommendation Levels**

| | *QRec* | n | *Rec* | *SUE* | *TACCR* | *CAPEX* | *MVE* | *EP* | *BTM* | *TURN* | *SG* | *LTG* | *FREV* | *MOM* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Worst | 0.00 | 4,517 | 3.02 | −0.100 | 0.000 | 0.090 | 8,946 | −0.040 | 0.560 | 0.100 | 1.000 | 10.07 | −0.010 | 0.000 |
| | 0.25 | 4,644 | 3.43 | −0.040 | 0.010 | 0.110 | 14,785 | 0.030 | 0.480 | 0.090 | 1.020 | 12.10 | 0.000 | 0.010 |
| | 0.50 | 4,887 | 3.68 | 0.000 | 0.010 | 0.120 | 20.937 | 0.040 | 0.430 | 0.090 | 1.620 | 13.13 | 0.001 | 0.010 |
| | 0.75 | 3,721 | 3.87 | 0.060 | 0.010 | 0.130 | 27,761 | 0.050 | 0.400 | 0.080 | 1.030 | 13.66 | 0.000 | 0.010 |
| Best | 1.00 | 5,765 | 4.18 | 0.250 | 0.010 | 0.130 | 26,614 | 0.050 | 0.360 | 0.080 | 1.040 | 15.92 | 0.000 | 0.030 |

**Panel B: Recommendation Changes**

| | *QChgRec* | n | *ChgRec* | *SUE* | *TACCR* | *CAPEX* | *MVE* | *EP* | *BTM* | *TURN* | *SG* | *LTG* | *FREV* | *MOM* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Down | 0.00 | 4,436 | −0.28 | −0.190 | 0.000 | 0.120 | 15,254 | 0.010 | 0.470 | 0.100 | 1.020 | 13.30 | −0.010 | 0.000 |
| | 0.25 | 4,183 | −0.09 | 0.050 | 0.010 | 0.120 | 22,946 | 0.030 | 0.440 | 0.080 | 1.020 | 13.03 | 0.000 | 0.010 |
| | 0.50 | 4,806 | −0.01 | 0.080 | 0.010 | 0.110 | 20,912 | 0.030 | 0.440 | 0.070 | 1.020 | 12.69 | 0.000 | 0.020 |
| | 0.75 | 4,612 | 0.06 | 0.190 | 0.010 | 0.120 | 24,420 | 0.040 | 0.420 | 0.090 | 1.660 | 13.12 | 0.000 | 0.010 |
| Up | 1.00 | 4,697 | 0.24 | 0.030 | 0.010 | 0.110 | 17,045 | 0.030 | 0.440 | 0.090 | 1.020 | 13.03 | 0.000 | 0.030 |

**Panel C: Short Interest Levels**

| | *QSIratio* | n | *SIratio* | *SUE* | *TACCR* | *CAPEX* | *MVE* | *EP* | *BTM* | *TURN* | *SG* | *LTG* | *FREV* | *MOM* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low | 0.00 | 4,370 | 0.6% | 0.100 | 0.010 | 0.090 | 43,012 | 0.040 | 0.470 | 0.050 | 1.020 | 11.10 | 0.000 | 0.010 |
| | 0.25 | 4,371 | 1.5% | 0.100 | 0.010 | 0.110 | 25,404 | 0.050 | 0.440 | 0.060 | 1.020 | 11.79 | 0.000 | 0.020 |
| | 0.50 | 4,370 | 2.3% | 0.000 | 0.010 | 0.130 | 15,789 | 0.040 | 0.430 | 0.070 | 1.020 | 12.70 | 0.000 | 0.020 |
| | 0.75 | 4,371 | 3.8% | 0.060 | 0.010 | 0.130 | 10,072 | 0.030 | 0.450 | 0.090 | 1.020 | 13.51 | 0.000 | 0.020 |
| High | 1.00 | 4,371 | 9.7% | −0.050 | 0.000 | 0.130 | 5,894 | 0.010 | 0.560 | 0.150 | 1.700 | 13.96 | −0.010 | 0.010 |

The samples consist of 23,534 (recommendations) and 21,853 (short-interest) firm-quarter observations, respectively during the period 2000–2013. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. *QRec* is the quintile assignment based on recommendation levels. *QChgRec* is the quintile assignment based on recommendation revisions. *QSIratio* is the quintile assignment based on short interest. *QRec*, *QChgRec*, and *QSIratio* are scaled to range between 0 and 1 (0.00, 0.25, 0.50, 0.75, 1.00) to facilitate the interpretation of the coefficients.

**TABLE 3**

**Use of Predictive Information by Analysts**

**Panel A: Explaining Recommendation Levels and Changes (Using Ordered Logistic Regression: Financial Information)**

| Recommendation Levels | | | | Recommendation Changes | |
|---|---|---|---|---|---|
| **Variable** | **Predict** | **Coefficient** | **z-stat** | **Coefficient** | **z-stat** |
| *Accounting* | | | | | |
| *SUE* | Pos | 0.016** | 2.08 | 0.008 | 1.30 |
| *TACCR* | Neg | 0.092 | 0.30 | 0.196 | 0.89 |
| *CAPEX* | Neg | 0.617 | 1.66 | −0.198** | −2.26 |
| *Valuation* | | | | | |
| *LNMVE* | Neg | 0.340*** | 7.93 | 0.018** | 2.26 |
| *EP* | Pos | 1.356*** | 4.21 | −0.104 | −1.83 |
| *BTM* | Pos | −0.434*** | −2.86 | −0.079** | −2.41 |
| *TURN* | Neg | −2.433*** | −4.51 | −0.432** | −2.21 |
| *Growth* | | | | | |
| *SG* | Neg | 0.000 | 0.60 | 0.000*** | 9.93 |
| *LTG* | Neg | 0.068*** | 8.04 | 0.002 | 1.05 |
| *Momentum* | | | | | |
| *FREV* | Pos | 2.405*** | 3.45 | 1.779*** | 4.15 |
| *MOM* | Pos | 0.138 | 0.90 | 0.519*** | 4.75 |
| Pseudo $R^2$ | | 0.073 | | 0.008 | |

*, **, *** Indicate statistical significance at the $\alpha = 0.10$, 0.05, and 0.01 levels, respectively, using a two-tailed test. n = 23,534 firm-quarters.

This table reports log-likelihood results when analysts' recommendation quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns. I do not report the intercepts for parsimony. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. The "Predict" column reports the predicted relation between the explanatory variable and future returns as indicated in prior research. I report test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month.

*(continued on next page)*

## TABLE 3
## Use of Predictive Information by Analysts

**Panel B: Explaining Recommendation Levels and Changes (Using Ordered Logistic Regression: Presence of Nonfinancial Information)**

| **Recommendation Levels** | | | | **Recommendation Changes** | |
|---|---|---|---|---|---|
| **Variable** | **Predict** | **Coefficient** | **z-stat** | **Coefficient** | **z-stat** |
| *NFM* | Pos | 0.127 | 1.39 | −0.003 | −0.12 |
| *Accounting* | | | | | |
| *SUE* | Pos | 0.016** | 2.10 | 0.008 | 1.30 |
| *TACCR* | Neg | 0.104 | 0.34 | 0.196 | 0.89 |
| *CAPEX* | Neg | 0.602 | 1.61 | −0.197** | −2.26 |
| *Valuation* | | | | | |
| *LNMVE* | Neg | 0.331*** | 7.59 | 0.018** | 2.26 |
| *EP* | Pos | 1.347*** | 4.21 | −0.104 | −1.83 |
| *BTM* | Pos | −0.436*** | −2.86 | −0.079** | −2.41 |
| *TURN* | Neg | −2.456*** | −4.50 | −0.432** | −2.21 |
| *Growth* | | | | | |
| *SG* | Neg | 0.000 | 0.44 | 0.000*** | 9.93 |
| *LTG* | Neg | 0.069*** | 8.07 | 0.002 | 1.05 |
| *Momentum* | | | | | |
| *FREV* | Pos | 2.409*** | 3.47 | 1.779*** | 4.15 |
| *MOM* | Pos | 0.134 | 0.87 | 0.519*** | 4.75 |
| Pseudo $R^2$ | | 0.073 | | 0.008 | |

*, **, *** Indicate statistical significance at the $\alpha$ = 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed test. n = 23,534 firm-quarters.

This table reports log-likelihood results when analysts' recommendation quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns and a variable of interest (NFM). I do not report the intercepts for parsimony. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. The "Predict" column reports the predicted relation between the explanatory variable and future returns as indicated in prior research. I report test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month.

*(continued on next page)*

**TABLE 3**

**Use of Predictive Information by Analysts**

**Panel C: Explaining Recommendation Levels and Changes (Using Ordered Logistic Regression: Direction of Nonfinancial Information)**

| **Recommendation Levels** | | | | **Recommendation Changes** | |
|---|---|---|---|---|---|
| **Variable** | **Predict** | **Coefficient** | **z-stat** | **Coefficient** | **z-stat** |
| *NFM* | Pos | 0.193*** | 2.03 | −0.013 | −0.51 |
| *UNFAV* | Neg | −0.366*** | −3.72 | 0.057 | 1.42 |
| *Accounting* | | | | | |
| *SUE* | Pos | 0.016** | 2.07 | 0.008 | 1.29 |
| *TACCR* | Neg | 0.108 | 0.36 | 0.200 | 0.91 |
| *CAPEX* | Neg | 0.610 | 1.63 | −0.198** | −2.25 |
| *Valuation* | | | | | |
| *LNMVE* | Neg | 0.324*** | 7.44 | 0.019** | 2.40 |
| *EP* | Pos | 1.326*** | 4.26 | −0.106 | −1.86 |
| *BTM* | Pos | −0.423*** | −2.81 | −0.080** | −2.46 |
| *TURN* | Neg | −2.398*** | −4.44 | −0.440** | −2.25 |
| *Growth* | | | | | |
| *SG* | Neg | 0.000 | 0.23 | 0.000*** | 9.85 |
| *LTG* | Neg | 0.069*** | 8.18 | 0.002 | 1.05 |
| *Momentum* | | | | | |
| *FREV* | Pos | 2.381*** | 3.42 | 1.783*** | 4.18 |
| *MOM* | Pos | 0.132 | 0.87 | 0.519*** | 4.75 |
| Pseudo $R^2$ | | 0.074 | | 0.008 | |

*, **, *** Indicate statistical significance at the $\alpha$ = 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed test. n = 23,534 firm-quarters.

This table reports log-likelihood results when analysts' recommendation quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns and variables of interest (NFM and *UNFAV*). For this regression, *NFM* estimates the log-likelihood of a firm both reporting the use of nonfinancial measures and reporting a positive (favorable) direction of those nonfinancial measures. I do not report the intercepts for parsimony. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. The "Predict" column reports the predicted relation between the explanatory variable and future returns as indicated in prior research. I report test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month.

**TABLE 4**

**Use of Predictive Information by Analysts**

**Panel A: Explaining Recommendation Levels and Changes (*Model 3*: Direction of Nonfinancial Measures)**

**Average Marginal Effects by Recommendation Levels (*QRec*)**

| Variable | Quintile=1 | Quintile=2 | Quintile=3 | Quintile=4 | Quintile=5 |
|---|---|---|---|---|---|
| *NFM* | -0.0267 | -0.0131 | 0.00119 | 0.00977 | 0.0289 |
| (se) | (0.0134) | (0.00641) | (0.00102) | (0.00493) | (0.0141) |
| *UNFAV* | 0.0540 | 0.0226 | -0.00537 | -0.0196 | -0.0516 |
| (se) | (0.0154) | (0.00570) | (0.00259) | (0.00559) | (0.0132) |
| *SUE* | -0.00223 | -0.00110 | 0.0000790 | 0.000806 | 0.00245 |
| (se) | (0.00109) | (0.000532) | (0.0000708) | (0.000394) | (0.00118) |
| *TACCR* | -0.0148 | -0.00731 | 0.000524 | 0.00535 | 0.0162 |
| (se) | (0.0416) | (0.0205) | (0.00152) | (0.0150) | (0.0456) |
| *CAPEX* | -0.0839 | -0.0415 | 0.00297 | 0.0303 | 0.0921 |
| (se) | (0.0516) | (0.0256) | (0.00284) | (0.0189) | (0.0564) |
| *MVE* | -0.0446 | -0.0220 | 0.00158 | 0.0161 | 0.0489 |
| (se) | (0.00618) | (0.00275) | (0.00117) | (0.00226) | (0.00627) |
| *EP* | -0.182 | -0.0901 | 0.00646 | 0.0659 | 0.200 |
| (se) | (0.0429) | (0.0216) | (0.00473) | (0.0156) | (0.0475) |
| *BTM* | 0.0582 | 0.0288 | -0.00206 | -0.0210 | -0.0639 |
| (se) | (0.0206) | (0.0105) | (0.00153) | (0.00754) | (0.0230) |
| *TURN* | 0.330 | 0.163 | -0.0117 | -0.119 | -0.362 |
| (se) | (0.0731) | (0.0379) | (0.00813) | (0.0261) | (0.0838) |
| *SG* | -0.00000379 | -0.00000187 | 0.000000134 | 0.00000137 | 0.00000416 |
| (se) | (0.0000163) | (0.00000805) | (0.000000591) | (0.00000589) | (0.0000179) |
| *LTG* | -0.00944 | -0.00467 | 0.000334 | 0.00341 | 0.0104 |
| (se) | (0.00116) | (0.000549) | (0.000239) | (0.000414) | (0.00125) |
| *FREV* | -0.327 | -0.162 | 0.0116 | 0.118 | 0.359 |
| (se) | (0.0957) | (0.0486) | (0.00874) | (0.0353) | (0.106) |
| *MOM* | -0.0182 | -0.00898 | 0.000643 | 0.00657 | 0.0199 |
| (se) | (0.0210) | (0.0104) | (0.000881) | (0.00759) | (0.0230) |

*(continued on next page)*

## Use of Predictive Information by Analysts

**Panel B: Explaining Recommendation Levels and Changes (*Model 3*: Direction of Nonfinancial Measures)**

**Average Marginal Effects by Recommendation Changes (QChgRec)**

| Variable | Quintile=1 | Quintile=2 | Quintile=3 | Quintile=4 | Quintile=5 |
|---|---|---|---|---|---|
| *NFM* | 0.00199 | 0.00102 | 0.0000967 | -0.00100 | -0.00210 |
| (se) | (0.00389) | (0.00200) | (0.000193) | (0.00196) | (0.00412) |
| *UNFAV* | -0.00861 | -0.00452 | -0.000542 | 0.00433 | 0.00934 |
| (se) | (0.00600) | (0.00321) | (0.000473) | (0.00301) | (0.00668) |
| *SUE* | -0.00127 | -0.000653 | -0.0000610 | 0.000642 | 0.00135 |
| (se) | (0.000985) | (0.000505) | (0.0000473) | (0.000496) | (0.00104) |
| *TACCR* | -0.0304 | -0.0156 | -0.00146 | 0.0153 | 0.0321 |
| (se) | (0.0336) | (0.0172) | (0.00160) | (0.0169) | (0.0354) |
| *CAPEX* | 0.0301 | 0.0154 | 0.00144 | -0.0152 | -0.0318 |
| (se) | (0.0134) | (0.00686) | (0.000677) | (0.00675) | (0.0141) |
| *MVE* | -0.00293 | -0.00150 | -0.000141 | 0.00148 | 0.00310 |
| (se) | (0.00123) | (0.000626) | (0.0000603) | (0.000619) | (0.00129) |
| *EP* | 0.0161 | 0.00824 | 0.000770 | -0.00809 | -0.0170 |
| (se) | (0.00864) | (0.00444) | (0.000424) | (0.00436) | (0.00912) |
| *BTM* | 0.0122 | 0.00626 | 0.000586 | -0.00615 | -0.0129 |
| (se) | (0.00495) | (0.00256) | (0.000257) | (0.00251) | (0.00524) |
| *TURN* | 0.0670 | 0.0343 | 0.00321 | -0.0337 | -0.0708 |
| (se) | (0.0299) | (0.0153) | (0.00144) | (0.0150) | (0.0315) |
| *SG* | -0.0000465 | -0.0000238 | -0.00000223 | 0.0000234 | 0.0000491 |
| (se) | (0.00000472) | (0.00000250) | (0.000000376) | (0.00000248) | (0.00000495) |
| *LTG* | -0.000293 | -0.000150 | -0.0000140 | 0.000147 | 0.000309 |
| (se) | (0.000278) | (0.000143) | (0.0000135) | (0.000140) | (0.000294) |
| *FREV* | -0.271 | -0.139 | -0.0130 | 0.137 | 0.287 |
| (se) | (0.0649) | (0.0334) | (0.00361) | (0.0331) | (0.0683) |
| *MOM* | -0.0791 | -0.0405 | -0.00379 | 0.0398 | 0.0836 |
| (se) | (0.0166) | (0.00857) | (0.000999) | (0.00842) | (0.0176) |

Standard errors in parentheses (se)
This table reports the marginal effect estimations when analysts' recommendation quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns and variables of interest (*NFM* and *UNFAV)*. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. *QRec* is the quintile assignment based on recommendation levels. *QChgRec* is the quintile assignment based on recommendation revisions. *QRec* and *QChgRec* are scaled to range between 0 and 1 (0.00, 0.25, 0.50, 0.75, 1.00), which correspond to Outcomes 1-5, respectively.

## TABLE 5

## Use of Predictive Information by Analysts

### Panel A: Explaining Recommendation Levels and Changes (Interaction between NFM Direction and Financials)

**Predicted Probabilities by Recommendation Levels (*QRec*)**

| VARIABLES | (1)<br>Quintile=5 | (2)<br>Quintile=5 | (3)<br>Quintile=5 | (4)<br>Quintile=5 |
|---|---|---|---|---|
| *UNFAV* x Financials | 0.280*** | 0.216*** | 0.280*** | 0.216*** |
| (Group 1) | (0.0142) | (0.0184) | (0.0142) | (0.0184) |
| *UNFAV* x Financials | 0.280*** | 0.280*** | 0.209*** | 0.209*** |
| (Group 2) | (0.0142) | (0.0142) | (0.0114) | (0.0114) |
| Observations | 18,598 | 18,598 | 18,598 | 18,598 |
| Difference | | 0.0642 | -0.0703 | -0.00617 |
| se | | (0.0163) | (0.0131) | (0.0203) |
| z-stat | | 3.943 | -5.370 | -0.304 |

| VARIABLES | (1)<br>Quintile=4 | (2)<br>Quintile=4 | (3)<br>Quintile=4 | (4)<br>Quintile=4 |
|---|---|---|---|---|
| *UNFAV* x Financials | 0.189*** | 0.170*** | 0.189*** | 0.170*** |
| (Group 1) | (0.00618) | (0.00847) | (0.00618) | (0.00847) |
| *UNFAV* x Financials | 0.189*** | 0.189*** | 0.167*** | 0.167*** |
| (Group 2) | (0.00618) | (0.00618) | (0.00524) | (0.00524) |
| Observations | 18,598 | 18,598 | 18,598 | 18,598 |
| Difference | | 0.0194 | -0.0218 | -0.00241 |
| se | | (0.00599) | (0.00425) | (0.00785) |
| z-stat | | 3.235 | -5.129 | -0.307 |

| VARIABLES | (1)<br>Quintile=3 | (2)<br>Quintile=3 | (3)<br>Quintile=3 | (4)<br>Quintile=3 |
|---|---|---|---|---|
| *UNFAV* x Financials | 0.229*** | 0.236*** | 0.229*** | 0.236*** |
| (Group 1) | (0.00617) | (0.00601) | (0.00617) | (0.00601) |
| *UNFAV* x Financials | 0.229*** | 0.229*** | 0.236*** | 0.236*** |
| (Group 2) | (0.00617) | (0.00617) | (0.00599) | (0.00599) |
| Observations | 18,598 | 18,598 | 18,598 | 18,598 |
| Difference | | -0.00625 | 0.00619 | -0.00006 |
| se | | (0.00230) | (0.00239) | (0.000196) |
| z-stat | | -2.714 | 2.591 | -0.292 |

Standard errors in parentheses

*, **, *** Indicate statistical significance at the $\alpha = 0.10$, 0.05, and 0.01 levels, respectively, using a two-tailed test.

This table reports the predicted probabilities by recommendation levels when analysts' recommendation quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns and variables of interest (*NFM* and *UNFAV)*. Models 1-4 compare the probabilities: **(1)** *UNFAV*=0, Financials (75th percentile) to *UNFAV*=0, Financials (75th percentile); **(2)** *UNFAV*=1, Financials (75th percentile) to *UNFAV*=0, Financials (75th percentile); **(3)** *UNFAV*=0, Financials (75th percentile) to *UNFAV*=0, Financials (50th percentile); **(4)** *UNFAV*=1, Financials (75th percentile) to *UNFAV*=0, Financials (50th percentile). I also conduct a significance test of the difference between the predicted probabilities and report both the standard error and z-stat.

**TABLE 5**

**Use of Predictive Information by Analysts**

**Panel B: Explaining Recommendation Levels and Changes (Interaction between NFM Direction and Financials)**

**Predicted Probabilities by Recommendation Change (*QChgRec*)**

| VARIABLES | (1)<br>Quintile=5 | (2)<br>Quintile=5 | (3)<br>Quintile=5 | (4)<br>Quintile=5 |
|---|---|---|---|---|
| *UNFAV* x Financials | 0.211*** | 0.220*** | 0.211*** | 0.220*** |
| (Group 1) | (0.00389) | (0.00735) | (0.00389) | (0.00735) |
| *UNFAV* x Financials | 0.211*** | 0.211*** | 0.205*** | 0.205*** |
| (Group 2) | (0.00389) | (0.00389) | (0.00329) | (0.00329) |
| Observations | 18,271 | 18,271 | 18,271 | 18,271 |
| Difference | | -0.00961 | -0.00511 | -0.0147 |
| se | | (0.00687) | (0.00303) | (0.00758) |
| z-stat | | -1.399 | -1.683 | -1.942 |

| VARIABLES | (1)<br>Quintile=4 | (2)<br>Quintile=4 | (3)<br>Quintile=4 | (4)<br>Quintile=4 |
|---|---|---|---|---|
| *UNFAV* x Financials | 0.209*** | 0.214*** | 0.209*** | 0.214*** |
| (Group 1) | (0.00403) | (0.00487) | (0.00403) | (0.00487) |
| *UNFAV* x Financials | 0.209*** | 0.209*** | 0.207*** | 0.207*** |
| (Group 2) | (0.00403) | (0.00403) | (0.00387) | (0.00387) |
| Observations | 18,271 | 18,271 | 18,271 | 18,271 |
| Difference | | -0.00422 | -0.00238 | -0.00661 |
| se | | (0.00293) | (0.00140) | (0.00326) |
| z-stat | | -1.444 | -1.696 | -2.028 |

| VARIABLES | (1)<br>Quintile=3 | (2)<br>Quintile=3 | (3)<br>Quintile=3 | (4)<br>Quintile=3 |
|---|---|---|---|---|
| *UNFAV* x Financials | 0.212*** | 0.211*** | 0.212*** | 0.211*** |
| (Group 1) | (0.00385) | (0.00388) | (0.00385) | (0.00388) |
| *UNFAV* x Financials | 0.212*** | 0.212*** | 0.212*** | 0.212*** |
| (Group 2) | (0.00385) | (0.00385) | (0.00386) | (0.00386) |
| Observations | 18,271 | 18,271 | 18,271 | 18,271 |
| Difference | | 0.000818 | 0.000313 | 0.00113 |
| se | | (0.000674) | (0.000201) | (0.000719) |
| z-stat | | 1.214 | 1.557 | 1.573 |

Standard errors in parentheses

*, **, *** Indicate statistical significance at the $\alpha = 0.10$, 0.05, and 0.01 levels, respectively, using a two-tailed test.

This table reports the predicted probabilities by recommendation changes when analysts' recommendation revision quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns and variables of interest (*NFM* and *UNFAV*). Models 1-4 compare the probabilities: **(1)** *UNFAV*=0, Financials (75th percentile) to *UNFAV*=0, Financials (75th percentile); **(2)** *UNFAV*=1, Financials (75th percentile) to *UNFAV*=0, Financials (75th percentile); **(3)** *UNFAV*=0, Financials (75th percentile) to *UNFAV*=0, Financials (50th percentile); **(4)** *UNFAV*=1, Financials (75th percentile) to *UNFAV*=0, Financials (50th percentile). I also conduct a significance test of the difference between the predicted probabilities and report both the standard error and z-stat.

**TABLE 6**

**Use of Predictive Information by Short Sellers**

**Panel A: Explaining Short Interest (Using Ordered Logistic Regression: Financial Information))**

| Variable | Predict | Short Interest Coefficient | z-stat |
|---|---|---|---|
| *Accounting* | | | |
| *SUE* | Neg | 0.004 | 0.82 |
| *TACCR* | Pos | 0.836 | 1.63 |
| *CAPEX* | Pos | −0.263 | −0.82 |
| *Valuation* | | | |
| *LNMV* | Pos | −0.796*** | −16.21 |
| *EP* | Neg | 0.167 | 0.70 |
| *BTM* | Neg | −0.668*** | −4.45 |
| *TURN* | Pos | 18.561*** | 13.27 |
| *Growth* | | | |
| *SG* | Pos | 0.002*** | 3.00 |
| *LTG* | Pos | 0.014** | 2.07 |
| *Momentum* | | | |
| *FREV* | Neg | 0.310 | 0.37 |
| *MOM* | Neg | −0.472*** | −2.87 |
| Pseudo $R^2$ | | 0.1775 | |

*, **, *** Indicate statistical significance at the $\alpha$ = 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed test. n = 21,853 firm-quarters.

This table reports log-likelihood results when short interest quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns. I do not report the intercepts for parsimony. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. The "Predict" column reports the predicted relation between the explanatory variable and future returns as indicated in prior research. I report test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month.

**TABLE 6**

**Use of Predictive Information by Short Sellers**

**Panel B: Explaining Short Interest (Using Ordered Logistic Regression: Presence of Nonfinancial Information)**

| **Variable** | **Predict** | **Short Interest** Coefficient | z-stat |
|---|---|---|---|
| *NFM* | Neg | −0.134 | −1.53 |
| *Accounting* | | | |
| *SUE* | Neg | 0.004 | 0.73 |
| *TACCR* | Pos | 0.826 | 1.62 |
| *CAPEX* | Pos | −0.245 | −0.76 |
| *Valuation* | | | |
| *LNMV* | Pos | −0.787*** | −15.94 |
| *EP* | Neg | 0.165 | 0.70 |
| *BTM* | Neg | −0.667*** | −4.45 |
| *TURN* | Pos | 18.619*** | 13.14 |
| *Growth* | | | |
| *SG* | Pos | 0.002*** | 3.08 |
| *LTG* | Pos | 0.013** | 1.97 |
| *Momentum* | | | |
| *FREV* | Neg | 0.306 | 0.37 |
| *MOM* | Neg | −0.473*** | −2.89 |
| Pseudo $R^2$ | | 0.1778 | |

*, **, *** Indicate statistical significance at the $\alpha$ = 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed test. n = 21,853 firm-quarters.

This table reports log-likelihood results when short interest quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns. I do not report the intercepts for parsimony. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. The "Predict" column reports the predicted relation between the explanatory variable and future returns as indicated in prior research. I report test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month.

**TABLE 6**

**Use of Predictive Information by Short Sellers**

**Panel C: Explaining Short Interest (Using Ordered Logistic Regression: Direction of Nonfinancial Information)**

| | | Short Interest | |
|---|---|---|---|
| **Variable** | **Predict** | **Coefficient** | **z-stat** |
| *NFM* | Neg | −0.167* | −1.89 |
| *UNFAV* | Pos | 0.205** | 2.10 |
| *Accounting* | | | |
| *SUE* | Neg | 0.004 | 0.74 |
| *TACCR* | Pos | 0.855* | 1.68 |
| *CAPEX* | Pos | −0.242 | −0.75 |
| *Valuation* | | | |
| *LNMV* | Pos | −0.784*** | −15.87 |
| *EP* | Neg | 0.163 | 0.70 |
| *BTM* | Neg | −0.675*** | −4.50 |
| *TURN* | Pos | 18.569*** | 13.12 |
| *Growth* | | | |
| *SG* | Pos | 0.002*** | 3.06 |
| *LTG* | Pos | 0.013** | 1.99 |
| *Momentum* | | | |
| *FREV* | Neg | 0.311 | 0.37 |
| *MOM* | Neg | −0.471*** | −2.88 |
| Pseudo $R^2$ | | 0.1781 | |

*, **, *** Indicate statistical significance at the $\alpha = 0.10$, 0.05, and 0.01 levels, respectively, using a two-tailed test. n = 21,853 firm-quarters.

This table reports log-likelihood results when short interest quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns. I do not report the intercepts for parsimony. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. The "Predict" column reports the predicted relation between the explanatory variable and future returns as indicated in prior research. I report test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month.

**TABLE 7**

**Use of Predictive Information by Short Sellers**

**Panel A: Explaining Short Interest (*Model 3*: Direction of Nonfinancial Measures)**

**Average Marginal Effects by Short Interest (*QSIratio*)**

| Variable | Quintile=1 | Quintile=2 | Quintile=3 | Quintile=4 | Quintile=5 |
|---|---|---|---|---|---|
| *NFM* | 0.0189 | 0.00866 | -0.0000290 | -0.00913 | -0.0184 |
| (se) | (0.00994) | (0.00471) | (0.000404) | (0.00485) | (0.00981) |
| *NUNFAV* | -0.0225 | -0.0109 | -0.000659 | 0.0108 | 0.0233 |
| (se) | (0.0104) | (0.00538) | (0.000811) | (0.00492) | (0.0115) |
| *SUE* | -0.000468 | -0.000210 | 0.00000127 | 0.000223 | 0.000452 |
| (se) | (0.000632) | (0.000284) | (0.0000100) | (0.000303) | (0.000610) |
| *TACCR* | -0.0974 | -0.0436 | 0.000265 | 0.0465 | 0.0942 |
| (se) | (0.0580) | (0.0260) | (0.00203) | (0.0276) | (0.0564) |
| *CAPEX* | 0.0276 | 0.0124 | -0.0000750 | -0.0132 | -0.0267 |
| (se) | (0.0367) | (0.0165) | (0.000573) | (0.0176) | (0.0356) |
| *MVE* | 0.0892 | 0.0400 | -0.000243 | -0.0427 | -0.0863 |
| (se) | (0.00497) | (0.00303) | (0.00187) | (0.00236) | (0.00613) |
| *EP* | -0.0185 | -0.00829 | 0.0000503 | 0.00884 | 0.0179 |
| (se) | (0.0266) | (0.0119) | (0.000390) | (0.0127) | (0.0258) |
| *BTM* | 0.0769 | 0.0344 | -0.000209 | -0.0367 | -0.0743 |
| (se) | (0.0171) | (0.00772) | (0.00161) | (0.00831) | (0.0164) |
| TURN | -2.114 | -0.947 | 0.00574 | 1.010 | 2.045 |
| (se) | (0.166) | (0.0806) | (0.0445) | (0.0960) | (0.127) |
| *SG* | -0.000205 | -0.0000919 | 0.000000557 | 0.0000980 | 0.000198 |
| (se) | (0.0000673) | (0.0000304) | (0.00000430) | (0.0000326) | (0.0000648) |
| *LTG* | -0.00150 | -0.000673 | 0.00000408 | 0.000718 | 0.00145 |
| (se) | (0.000755) | (0.000340) | (0.0000315) | (0.000358) | (0.000735) |
| *FREV* | -0.0354 | -0.0159 | 0.0000963 | 0.0169 | 0.0343 |
| (se) | (0.0945) | (0.0423) | (0.000792) | (0.0452) | (0.0914) |
| *MOM* | 0.0536 | 0.0240 | -0.000146 | -0.0256 | -0.0519 |
| (se) | (0.0188) | (0.00837) | (0.00113) | (0.00896) | (0.0181) |

Standard errors in parentheses (se)

This table reports the marginal effect estimations when analysts' recommendation quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns and variables of interest (*NFM* and *UNFAV)*. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. *QSIratio* is the quintile assignment based on short interest and is scaled to range between 0 and 1 (0.00, 0.25, 0.50, 0.75, 1.00).

**TABLE 8**

**Use of Predictive Information by Short Sellers**

**Explaining Short Interest (Interaction between NFM Direction and Financials)**

**Predicted Probabilities by Short Interest (*QSIratio*)**

| VARIABLES | (1) Quintile=5 | (2) Quintile=5 | (3) Quintile=5 | (4) Quintile=5 |
|---|---|---|---|---|
| *UNFAV* x Financials (Group 1) | 0.107*** | 0.128*** | 0.107*** | 0.128*** |
| | (0.00832) | (0.0137) | (0.00832) | (0.0137) |
| *UNFAV* x Financials (Group 2) | 0.107*** | 0.107*** | 0.111*** | 0.111*** |
| | (0.00832) | (0.00832) | (0.00726) | (0.00726) |
| Observations | 17,403 | 17,403 | 17,403 | 17,403 |
| Difference | | -0.0209 | 0.00412 | -0.0168 |
| se | | (0.0106) | (0.00790) | (0.0135) |
| z-stat | | -1.961 | 0.522 | -1.239 |

| VARIABLES | (1) Quintile=4 | (2) Quintile=4 | (3) Quintile=4 | (4) Quintile=4 |
|---|---|---|---|---|
| *UNFAV* x Financials (Group 1) | 0.232*** | 0.257*** | 0.232*** | 0.257*** |
| | (0.0110) | (0.0145) | (0.0110) | (0.0145) |
| *UNFAV* x Financials (Group 2) | 0.232*** | 0.232*** | 0.237*** | 0.237*** |
| | (0.0110) | (0.0110) | (0.00836) | (0.00836) |
| Observations | 17,403 | 17,403 | 17,403 | 17,403 |
| Difference | | -0.0248 | 0.00527 | -0.0196 |
| se | | (0.0116) | (0.0101) | (0.0150) |
| z-stat | | -2.143 | 0.520 | -1.302 |

| VARIABLES | (1) Quintile=3 | (2) Quintile=3 | (3) Quintile=3 | (4) Quintile=3 |
|---|---|---|---|---|
| *UNFAV* x Financials (Group 1) | 0.282*** | 0.281*** | 0.282*** | 0.281*** |
| | (0.00854) | (0.00843) | (0.00854) | (0.00843) |
| *UNFAV* x Financials (Group 2) | 0.282*** | 0.282*** | 0.282*** | 0.282*** |
| | (0.00854) | (0.00854) | (0.00840) | (0.00840) |
| Observations | 17,403 | 17,403 | 17,403 | 17,403 |
| Difference | | 0.000263 | 0.000354 | 0.000617 |
| se | | (0.00210) | (0.000822) | (0.00155) |
| z-stat | | 0.125 | 0.431 | 0.398 |

Standard errors in parentheses

*, **, *** Indicate statistical significance at the $\alpha = 0.10$, 0.05, and 0.01 levels, respectively, using a two-tailed test.

This table reports the predicted probabilities when short interest quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns and variables of interest (*NFM* and *UNFAV*). Models 1-4 compare the probabilities: **(1)** *UNFAV*=0, Financials (75th percentile) to *UNFAV*=0, Financials (75th percentile); **(2)** *UNFAV*=1, Financials (75th percentile) to *UNFAV*=0, Financials (75th percentile); **(3)** *UNFAV*=0, Financials (75th percentile) to *UNFAV*=0, Financials (50th perct); **(4)** *UNFAV*=1, Financials (75th percentile) to *UNFAV*=0, Financials (50th percentile). I also conduct a significance test of the difference between the predicted probabilities and report both the standard error and z-stat.

Vita

Thomas F. Lewis, Jr. was born on May 24, 1975, in Norfolk, Virginia, and is an American citizen. He graduated from Kempsville High School, Virginia Beach, Virginia in 1992. He received his Bachelor of Science in Accounting from Norfolk State University, Norfolk, Virginia in 1996 and subsequently worked in public accounting in Chicago for three years. He received a Master of Business Administration from University of Chicago, Booth School of Business in 2002.