How the Interplay between Financial and Non-Financial Measures Affects Management Forecasting Behavior

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ABSTRACT: This study examines how the interplay between financial and non-financial measures affects management forecasting behavior. Building on the knowledge that NFMs are typically aligned with actual earnings and are likely incorporated into earnings forecasts, we investigate if the level of divergence between changes in NFMs and contemporaneous changes in earnings influences management forecasting behavior. We hand-collect company-specific NFMs (e.g., number of retail outlets, square footage of facilities, patents) disclosed in 10-K filings and describe how a greater divergence between NFMs and earnings (i.e., NFM changes substantially outpacing earnings growth, or vice versa) renders NFMs less useful for forecasting. As such, in more divergent settings, we observe that management is less likely to issue guidance. Consistent with our theory, for managers that do provide guidance in more divergent settings, management forecast errors increase. Last, we provide evidence that external stakeholders can use the level of divergence between NFMs and earnings to predict future management forecasting behavior. Our evidence demonstrates that NFMs and their relation with financial information play an important role in explaining management forecasting behavior.

Keywords: earnings guidance, forecast errors, management forecasts, non-financial measures
JEL Classification: G14, M40, M41

Data availability: *The data used in this study are publicly available from the sources indicated in the text.*

INTRODUCTION

This study examines how the interplay between financial and non-financial measures (NFMs) affects management forecasting behavior. Consistent with Brazel, Jones, and Zimbelman (2009) and Dechow, Larson, and Sloan (2011), we use the term non-financial measures (NFMs) to represent quantitative, capacity/performance-related measures that are expected to have a positive contemporaneous relation with growth in revenues and/or earnings. Building on the knowledge that NFMs are typically aligned with actual earnings and likely incorporated into earnings forecasts (e.g., Baginski, Hassell, and Kimbrough 2004; Curtis, Lundholm, and McVay 2014), we investigate how changes in both NFMs and contemporaneous earnings affect management forecasting behavior.

The level of divergence between changes in NFMs and changes in contemporaneous earnings represents incremental information about the firm's investment choices (e.g., increasing employee headcount, number of stores, facility size) that are not recognized in the firm's earnings. As the level of divergence increases, NFM changes substantially outpace actual earnings changes (or vice versa), and management may need to provide additional clarity to investors. Alternatively, in more divergent settings, NFMs are not aligned with earnings and thus may be a less useful input for management forecast models. We therefore investigate if a greater divergence influences whether management chooses to provide earnings guidance. For managers that do choose to forecast under divergent conditions, we also determine whether forecast accuracy suffers. As such, the objective of this study is to empirically examine if the level of divergence between NFMs and earnings influences management forecasting behavior.[1]

[1] We operationalize "management forecasting behavior" separately as the likelihood of management issuing a forecast and forecast error.

Companies disclose quantitative NFMs related to performance or capacity (e.g., number patents or customers) along with financial statements in 10-K filings (Brazel et al. 2009). NFMs reported in the Management Discussion and Analysis section of the 10-K should reveal information about the company's strategy, its current and future performance, and its ability to meet future accounting outcomes such as analysts' forecasts (SEC 1989). For example, retailers disclose the number of stores they operate, manufacturers discuss production capacity, and service providers offer the number of customers served. In instances where a clear link exists between NFMs and financial performance, managers and analysts may build revenue and earnings models using NFMs to develop both internal and external forecasts (Koller, Goedhart, and Wessels 2005; Curtis et al. 2014).

A primary objective of financial accounting is to record, classify, and summarize economic events to provide financial information for decision-making (Bell, Peecher, and Solomon 2005; FASB 2010, para. OB2; Arens, Elder, and Beasley 2010). Companies disclose NFMs that reflect key aspects of company performance/capacity and measure economic activity (Francis, Philbrick, and Schipper 2003; Schultz, Bierstaker, and O'Donnell 2010). Prior research suggests a relatively consistent (versus divergent) relation between investments and divestments in NFMs and contemporaneous earnings changes. For example, Brazel et al. (2009) observe that the average difference between changes in employees and changes in contemporaneous revenue is only 4%.[2] When a company's NFM changes substantially outpace its actual earnings changes (or vice versa), the company is exhibiting a *more divergent* relation. In these settings, the impact

[2] While Brazel et al. (2009) provide small-sample (n = 50) evidence in support of the assumption that NFMs and earning changes are positively correlated (or aligned), we illustrate in Figure 1 that as the *divergence* between actual earnings changes and contemporaneous NFM changes *increases*, the number of companies exhibiting such a relation *decreases*. Further, Table 3 illustrates that the mean difference between changes in actual earnings and changes in NFMs (*DIFF*) for our sample is only –1.76%. Last, the first regression of Table 9 shows that actual changes in NFMs are positively associated with actual changes in reported earnings (*%CHANGE_EPS*). Thus, while we rely on the assumption that NFMs and actual earnings are typically aligned, we also provide empirical evidence in support of this notion.

of NFM changes on earnings growth is less clear, and investor concerns about the validity of the financial results or the operational efficiency of the company could arise (Brazel et al. 2009). To reduce such uncertainty, managers could be incentivized to voluntarily release earnings forecasts during the course of the year to signal to investors how changes in the company's NFMs will ultimately be reflected in earnings (Trueman 1986).

On the other hand, because changes in NFMs and earnings are typically aligned, management is accustomed to using expected or observed changes in NFMs to predict *similar* growth rates for earnings. In a more divergent setting, management faces an atypical relation between a forecast input (NFMs) and what is being forecasted (earnings). Thus, when NFMs and earnings exhibit divergent patterns, the usefulness of NFMs as a forecast input may be impaired. Disclosure theory indicates that as the usefulness of management's internal information set decreases, they are less likely to provide voluntary disclosures about the company's operations (Diamond 1985; Trueman 1986; Verrecchia 1990).

We test these competing arguments by examining the relation between the level of NFM/earnings divergence and the likelihood that management issues an earnings forecast. Regardless of management's incentives or abilities to compile information into a forecast, forecasts based on lower-quality inputs will likely be less accurate (e.g., Dorantes, Li, Peters, and Richardson 2013). Thus, we investigate if management forecast errors are larger under more divergent conditions.

To examine our hypotheses, we hand-collect numerous company-specific, year-end NFM disclosures from 10-K filings across many industries. We then examine how the level of divergence between NFMs and contemporaneous earnings affects the forecasting behavior of managers. For our sample of firms, we measure the level of divergence with the variable "DIFF", which is the difference between a company's change in actual earnings and its median change in actual NFMs for the same year. We observe that as the *absolute value* of *DIFF* increases (i.e., less typical conditions where investment choices are not recognized in the firm's earnings), managers are less likely to issue forecasts. Divergence between NFMs and earnings likely renders NFMs a less diagnostic input for forecasts. Managers, concerned that their reputation will be hurt by inaccurate forecasts, are less likely to issue forecasts. Consistent with this notion, when management provides earnings guidance under more divergent conditions, we find that management forecast errors increase.

Prior studies examining inconsistencies between financial and non-financial measures have either examined small sample sizes due to the labor intensive hand-collection of NFMs (Brazel et al. 2009) or employed only one type of NFM (e.g., employee headcount; Dechow et al. 2011). We contribute to the NFM literature by collecting numerous company-specific NFM disclosures across a variety of industries and develop a standardized measure of how a firm's investment choices are and are not recognized in the firm's earnings (i.e., how NFMs and earnings diverge). By doing so, we extend the NFM literature to the *forecast* setting by examining management forecasting behavior under divergent conditions.

We demonstrate that managers are hesitant to issue guidance in the divergent setting, consistent with the notion that their ability to issue accurate forecasts is impaired due to less predictive NFMs. Despite the incentive for managers to issue a forecast in divergent settings to appease investor concerns, the reputational concerns of inaccurate forecasts appear to overwhelm this incentive. Also, our results for forecast accuracy show that those who *use* management forecasts should be cautious of forecasts issued under divergent conditions.[3] Last, in additional analyses we determine that the level of NFM/earnings divergence can be used by stakeholders as an early indicator of whether management will issue forecasts in the *next* fiscal year and whether those forecasts will be accurate.

The remainder of our paper is organized as follows: the next section discusses the related literature and develops hypotheses; we then describe our research method and the results of our empirical tests; the final section concludes.

MOTIVATION AND DEVELOPMENT OF HYPOTHESES

NFM disclosures are gaining recognition for their importance to financial statement users and those that regulate financial reporting (Black, Christensen, Kiosse, and Steffen 2015). For example, popular press coverage of the IPO filing by Facebook was directed at both the company's financial performance (e.g., sales growth) and its related NFMs (e.g., number of active users, employees, click-through rate) (e.g., Raice 2012). Recent articles concerning Google and Netflix discuss "revenue per click" and compare revenue and subscriber growth, respectively (Nicas 2017; Hufford 2017). While regulators and investors want to ensure that these NFMs directly relate to company performance, companies claim that knowledge of these NFMs is essential to understanding the business.[4]

Traditional NFMs such as the number of retail stores, production space, and employee headcount can be viewed as surrogate measures of economic activity (Brazel et al. 2009). Most studies examining the relation between NFMs and financial performance have demonstrated that NFMs are useful in predicting *future* (versus contemporaneous) financial performance. These

[3] Regarding investors being informed about divergent conditions at companies, see Jakab (2014) for an example of the popular press identifying a divergent pattern between Facebook Inc.'s advertising revenue growth and growth in its user base (NFM). Koh (2015) makes the same comparison for Twitter Inc.

[4] http://online.wsj.com/article/SB10001424127887324073504578114953782230548.html.

studies have also typically examined only one industry or a specific type of NFM. For example, Bonacchi, Kolev, and Lev (2014) develop a measure of customer franchise value for subscription-based companies and demonstrate that the measure is positively associated with future earnings.[5]

Some related research empirically tests whether NFMs, or more specifically, changes in NFMs, lead to comparable changes in *contemporaneous* financial performance. Brazel et al. (2009) illustrate that the mean difference between revenue growth and contemporaneous growth in NFMs (e.g., patents, number of products) ranges from 4 to 11%. Likewise, they demonstrate a strong, positive relation between one form of NFMs, changes in employee headcount, and contemporaneous changes in revenue. Dechow et al. (2011) find that the mean difference between changes in revenues (*assets*) and changes in order backlogs (*employees*) is 6% (*16%*). Finally, Curtis et al. (2014) study the retail industry and develop an accurate model for sales based on contemporaneous NFM data (e.g., store openings). While not perfectly aligned, the evidence suggests that changes in NFMs that occur during the year are positively related to contemporaneous changes in the financial statements.

If changes in NFMs reflect a change in the company's capacity or performance that will be reflected in earnings, managers would most likely incorporate those changes into earnings forecasts (Trueman 1986; Goodman, Neamtiu, Shroff, and White 2014).[6] Baginski et al. (2004) analyze managers' explanations as to what factors influence their forecasts. For 43% of their sample, managers provide internally-based factors as drivers of their forecasts, including new

[5] See Luft (2009) for a review of NFM-related literature in accounting. In addition, recent research has examined the quality of management *forecasts* of NFMs (versus the actual NFM disclosures used in this study). Specifically, Cole and Jones (2015) study the attributes (e.g., bias, explanatory power) of retailers' forecasts of planned capital expenditures and store openings.

[6] For example, Rent-A-Center stated in a press release that the company expected 2013 earnings in the range of $3.03 to $3.15 per share, with revenue growth estimated at 3 percent. The company also noted that it expected to open about 365 domestic RAC Acceptance kiosks and 60 rent-to-own store locations in Mexico. http://investor.rentacenter.com/phoenix.zhtml?c=90764&p=irol-newsarticle&ID=1839742.

products and investments in plant assets. NFMs such as these can therefore be viewed as quantifiable/observable outcomes resulting from management's plans and strategies (Baginski et al. 2004). When a retailer strategically plans or observes increases in stores, products, or employees, we would expect management to provide earnings forecasts during the year that reflect the NFM growth.[7]

The focus of our study is to examine if the interplay between NFMs and earnings influences management forecasting behavior. Changes in NFMs and earnings can exhibit either a consistent or divergent relation. The results of Brazel et al. (2009) and Dechow et al. (2011), suggest that changes in NFMs and actual earnings are typically consistent or *aligned*. For example, on average, a 10% expansion of stores, products, and employee headcount should lead to earnings growth of approximately 10%. When a company exhibits an atypical, more *divergent* relation, the divergence represents incremental information about the firm's investment choices (e.g., increasing employee headcount, number of stores, facility size) that have not been recognized in the firm's earnings. Growth in NFMs that substantially outpace the contemporaneous growth in earnings may lead investors to question the operational efficiency of the company, managers' control over the production process, and management's overall strategy. As stores open or new plants are built, investors would expect to see an improvement in

[7] Still, there are multiple reasons why NFM changes and contemporaneous changes in earnings may not be aligned. For example, NFM additions or contractions (e.g., store openings and closings) could occur either early or late in the fiscal year. We are unable to account for the timing of NFM additions/contractions in our analyses because 10-K disclosures (our data source) typically do not provide the timing of NFM changes. Likewise, our measure of NFM/earnings divergence does not account for different firms or industries that experience different conversion rates between investments in NFMs and earnings changes (e.g., the effect of a patent on earnings could differ between the healthcare and consumer goods industries). Last, we do not incorporate into our analyses the possibility that certain NFMs may interact such that their joint effect on earnings exceeds the changes in the individual NFMs (e.g., simultaneously increasing the number of product patents and stores). The examination of such interactions between NFM investments represents a fruitful area for future research. However, such customizations of our measure of NFM/earnings divergence would preclude us from developing a standardized measure that incorporates numerous company-specific NFM disclosures across a variety of industries. To address concerns about how NFMs may align with earnings, we test the assumption that actual NFM changes are significantly associated with contemporaneous changes in actual earnings. We also test the assumption that managers incorporate NFMs into their forecasts (see the section titled "Testing of Assumptions").

contemporaneous earnings. Management of the company may understand why the relation between NFMs and earnings has diverged and has an incentive to provide clarity to investors (Trueman 1986).[8]

When changes in earnings substantially outpace changes in NFMs, investors may also question the integrity of the company's financial reporting process/reliability of the earnings number (e.g., the use of accruals to bolster reported performance as described by Dichev et al. (2013)). Indeed, research in this area finds that companies committing fraudulent financial reporting typically exhibit financial growth that is not supported by contemporaneous growth in NFMs (Brazel et al. 2009; Dechow et al. 2011).[9] In circumstances where suspicion of fraud or low earnings quality exist, managers may attempt to alleviate the situation by providing guidance to the market.[10] On the other hand, Francis, Nanda, and Olsson (2008) observe that the quality of the firm's earnings is unrelated to whether a firm forecasts earnings.

As prior research suggests, management is likely accustomed to using expected or observed changes in NFMs to forecast *similar* growth rates for earnings. Thus, in more divergent settings, management faces an atypical relation between a forecast input (NFMs) and what is

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[8] See footnote 6 for an example of a forecast where financial and NFM growth patterns are discussed as part of an earnings forecast. We measure alignment/divergence between earnings and NFMs by comparing a company's change in actual earnings to its median change in NFMs over that same period. We associate larger (*smaller*) absolute differences between earnings and NFM changes with more divergent (*aligned*) settings.

[9] Alternatively, when such a divergence exists, investors could question the validity of the NFMs reported by management. However, see Brazel et al. (2009) for a discussion of how it would be difficult for management to manipulate reported NFMs (and how their results support this notion).

[10] An appropriate example is the four-year (2010-2014) SEC investigation of Keurig Green Mountain Inc.'s (GMCR) revenue recognition practices. In October of 2011, Greenlight Capital began making the case for short-selling GMCR's stock (which was previously valued at a high of $107.90 on 9/6/11), and Greenlight publicly questioned GMCR's accounting practices and decision to stop disclosing key NFM data (e.g., pounds of coffee sold) (see slide 21 of the presentation available at: http://online.wsj.com/public/resources/documents/EinhornGMCRpresentation_Oct2011_VIC.pdf). Despite and perhaps related to these concerns, the company *issued earnings guidance throughout the SEC investigation*. Subsequent to the start of the SEC investigation, a class action lawsuit related to improper accounting practices was filed. GMCR has since restated its financial statements from 2007-2010, the founder and chairman of GMCR has been fired, and its revenue recognition practices continued to be questioned by investors (for example, see https://www.forbes.com/sites/greatspeculations/2011/06/23/green-mountain-coffees-trouble-with-bean-counting/#1ae2db2796dc. The SEC closed its investigation in October, 2014 without issuing an enforcement action.

being forecasted (earnings). For example, in more divergent settings, the effects of current-year investments in NFMs may not be evident in earnings until future periods (if ever). Thus, when NFMs and earnings diverge, the usefulness of NFMs as a forecast input for contemporaneous earnings may be impaired.

Under divergent conditions, managers could employ alternative information sources or rely more on the non-NFM inputs (e.g., actions of competitors (Baginski et al. 2004)). Still, as the usefulness of management's internal information *set* decreases, they are less likely to provide voluntary disclosures about the company's operations (Diamond 1985; Trueman 1986; Verrecchia 1990). Indeed, managers are concerned about their forecasting reputations (Graham, Harvey, and Rajgopal 2005), and they may face market penalties for releasing low quality forecasts (Dorantes et al. 2013). Thus, more divergent settings may reduce the likelihood that management releases an earnings forecast.[11]

In sum, greater divergence between changes in NFMs and contemporaneous earnings could either (1) incentivize management to issue a forecast to provide clarity to concerned investors, or (2) render NFMs less useful for forecasting earnings and, due to concerns about accuracy, reduce the likelihood that management releases a forecast. Given these conflicting incentives, we state our first hypothesis in the null form:

H1: The level of divergence between changes in NFMs and changes in contemporaneous earnings will not be associated with the likelihood that an earnings forecast is released.

Regardless of management's incentives or ability to compile information into an earnings forecast, forecasts based on lower quality inputs are expected to be less accurate. Both Feng, Li,

[11] In addition to the level of divergence between NFMs/earnings, management's prior forecasting history affects the likelihood that an earnings forecast is released, as well as other forecast behavior (Tang, Yao, and Zarowin 2014). As such, in our tests of H1 and H2 we control for management's prior forecasting history. In additional analyses, we examine if the relation between the level of divergence and the likelihood that management issues guidance is conditional on management's forecasting history.

and McVay (2009) and Li, Peters, Richardson, and Watson (2011) illustrate that the accuracy of management earnings guidance is impaired by a weak internal control system that provides managers with erroneous and/or less timely internal reports. Like effective internal controls over financial reporting, the implementation of an enterprise system (versus legacy systems) enhances the information set available to management (Davenport 1998). Consistent with this notion, Dorantes et al. (2013) show that companies adopting enterprise systems issue more accurate forecasts of earnings.

Management forecasts of financial data that incorporate diagnostic, *non-financial* information will likely be more accurate (Dorantes et al. 2013). For example, positive customer relations can assist managers in predicting sales more accurately, and good supplier relations promote accurate cost of goods sold forecasts (Fairfield, Sweeney, and Yohn 1996; Lundholm and Sloan 2006). However, when contemporaneous changes in NFMs and earnings *diverge*, management's ability to use changes in NFMs to accurately forecast contemporaneous earnings may be impaired. Greater divergence suggests a lack of control over how investments (or divestments) in NFMs will ultimately be reflected in financial performance. When NFMs and earnings patterns diverge, the operational performance of a company is less aligned with the company's reported financial performance. As noted above, while greater divergence may either motivate or deter management to compile and release earnings forecasts (H1), less diagnostic NFMs in more divergent settings should lead to greater forecast errors, leading to our second hypothesis:

H2: As the level of divergence between changes in NFMs and changes in contemporaneous earnings increases, management forecast errors increase.

METHOD

Our paper is a convergence of two primary data sets: (1) hand-collected NFMs disclosed in company 10-Ks, and (2) management's annual forecasts from the Thomson First Call database.[12] We also collected annual financial data from the Compustat Fundamental database, monthly returns data from CRSP, and annual analysts' forecasts from I/B/E/S. The hand-collection of NFMs was aided by a website designed to identify quantitative, capacity/performance-related NFMs disclosed in companies' 10-Ks.[13] Consistent with Brazel et al. (2009) and Dechow et al. (2011), we focused our collection efforts on NFMs that were expected to have a *positive* contemporaneous relation with growth in revenues and/or earnings; thus, not every NFM disclosed in the 10-K was a candidate for our study.[14] For example, we excluded data related to interest rates. Along with the hand-collected NFMs, we also included employees (from Compustat), which is a common NFM disclosed by most companies. We rely on the median year-over-year percentage change across the NFMs to measure the overall direction and magnitude of a company's NFM performance. Therefore, each observation required two years of comparable NFM data to be considered an observation in our sample. In addition, we required at least three different NFMs for each company to provide a reasonable measure of the median change.

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[12] Chuk, Matsumoto, and Miller (2013) demonstrate the existence of systematic coverage biases for the First Call earnings forecasts. As they discuss, the bias is mostly attributed to earlier years that precede our sample period substantially. To avoid coverage bias, we searched the LEXIS-NEXIS database for any companies we considered "non-forecasters" for our sample and found only two exceptions. Our results are unchanged when removing these two companies.

[13] The website was developed in conjunction with the Financial Industry Regulatory Authority (FINRA) Investor Education Foundation.

[14] Consistent with our collection efforts, the majority of the NFMs collected for this study were positively correlated with the given firm's current-year earnings growth. For our sample of 659 companies, on average, 87% of a given firm's NFMs changed in the same direction as its earnings change (either positive or negative). While we excluded NFMs that were not capacity-related, we did not intentionally exclude NFMs that had a negative correlation with earnings growth (e.g., facilities or product investments with long-term, non-contemporaneous earnings impacts). We acknowledge that our results are derived from a sample dominated by NFMs that exhibit a positive contemporaneous relation with earnings changes. As such, our results may not convey to settings where management predominantly relies on NFMs that have an *inverse* relation with earnings to forecast earnings.

To obtain the NFMs, we used the aforementioned website that accessed10-Ks for publicly traded companies for the years 2007-2009.[15] To streamline hand-collection efforts while developing a representative sample, we focused on companies with the largest market capitalization in each of the Fama-French 30 industries (Fama and French 1997). We identified 1,164 candidate companies that covered at least 90% of the market capitalization in every industry. From these companies, we used the website and hand collected the same set of NFMs across two years for 747 of the companies. Observations were lost because: (1) the inability to collect at least three NFMs or (2) the inability to collect the same NFMs for both years.

Merging our hand-collected sample with Compustat, CRSP, and I/B/E/S to measure the necessary dependent and control variables for our models resulted in a loss of an additional 88 companies. Panel A of Table 1 shows the industry breakdown for each of the 659 unique companies in our sample period. Panel A also shows the percentage of market capitalization collected for each industry.

In total, we have 3,786 NFMs (Panel B) across the 659 companies – an average of six NFMs per company. Employees are available for every company in our sample, and the next largest category is Facilities, representing 17% of the NFMs collected. In the cross-section, each category captures a significant amount of companies so that no type of NFM or category dominates our study. Further, in Panel C we provide a cross-sectional view of our industry and NFM data from the first two panels, providing the number of NFM categories covered by companies within each industry. As shown, companies across most industries in our sample

[15] We recognize that the timing of our hand-collected sample corresponds with a global financial crisis beginning in 2008. As a result, we perform untabulated sensitivity tests incorporating Zmijewski's (1984) bankruptcy score as an additional control variable, and find that the results for our hypotheses are unchanged. The bankruptcy score is not significant for each test of our hypotheses, and the main variable of interest remains significant. Additionally, we remove four companies that went bankrupt within three years after our sample period, and results remain unchanged.

disclose NFMs across many categories; only seven of the thirty industries have coverage across less than eight categories of NFMs. Overall, Table 1 illustrates our ability to capture many NFMs across multiple industries and several NFM categories – a complement to previous NFM studies which have typically focused on one industry and/or one type of NFM.

For our sample of 659 companies, 340 have issued point or range management forecasts during our sample period. We use the larger sample of 659 companies to test the decision to provide a management forecast (H1) and the reduced sample of 340 companies to examine management forecast accuracy (H2).

Issuing Guidance (H1)

Building on the knowledge that NFMs are typically aligned with actual earnings and likely incorporated into earnings forecasts, our first hypothesis examines how divergence between NFMs and contemporaneous earnings influences management's decision to issue guidance (*GUIDANCE*). As stated previously, the level of divergence between NFMs and actual earnings (*DIFF*) represents incremental information about the firm's investment choices (e.g., increasing employee headcount, number of stores, facility size) that are not recognized in the firm's earnings. Our ability to capture many NFMs across multiple industries and several NFM categories allows us to develop a standardized measure for the level of divergence. We use the difference between changes in earnings and changes in NFMs to measure *DIFF* as follows:

$$DIFF_{i,t} = \%CHANGE\_EPS_{i,t} - \%MEDCHGNFM_{i,t} \quad (1a)$$

$$ABS\_DIFF_{i,t} = |DIFF_{i,t}| \quad (1b)$$

%CHANGE_EPS is the % change in actual earnings per share from I/B/E/S in year *t*. Our proxy for information contained in NFMs is the median percentage change in NFMs

(*%MEDCHGNFM)*.[16] By using the median percentage change, as opposed to the average change, we avoid the undue influence of one NFM's percentage change. Further, individual changes in NFMs will not be perfectly correlated, but the expectation is that the median change will capture the general direction and magnitude of a company's non-financial performance. *%MEDCHGNFM* is measured from the end of period *t-1* to the end of period *t*. We also measure changes in NFMs as: (1) the *average* change in NFMs, and (2) the change in employees. The average change is an alternative measurement option to using the median, while the change in employees provides one NFM measure consistent across all companies in the sample and removes any selection bias. Neither of these alternative measures alter our main findings as shown in the tables.

On average, *DIFF* is expected to be close to zero as changes in earnings are expected to be aligned with changes in NFMs (e.g., Brazel et al. 2009; Dechow et al. 2011). In Figure 1, we illustrate that the frequency distribution of *DIFF* for our sample of companies is centered near zero (i.e., earnings growth and NFM growth are consistent), and extreme outliers, both positive and negative, are less common. When focusing on the magnitude of divergence, we rely upon the absolute value of *DIFF* (*ABS_DIFF*). Larger (*smaller*) absolute value differences between earnings and NFM changes are representative of the more divergent (*aligned*) setting described in the development of H1 and H2. We use *ABS_DIFF* (vs. signed *DIFF*) because we predict that the level of divergence *in general*, both positive and negative differences, will affect forecasting

[16] With respect to levels versus changes, our use of changes reflects the analyses performed by Brazel et al. (2009). The focus of our study is how the level of divergence between changes in NFMs and changes in contemporaneous earnings impacts management forecasting behavior. The level of divergence represents incremental information about the firm's investment choices (e.g., increasing employee headcount, number of stores, facility size) that are not recognized in the firm's earnings. We believe that NFM changes (vs. levels) reflect/measure these "choices" and in Table 9 we demonstrate that these NFM changes impact earnings changes.

behavior.[17] The Appendix provides an example from our sample for the calculations of *%MEDCHGNFM*, *DIFF*, and *ABS_DIFF*.

We use the following logit model to examine the likelihood of managers to issue guidance when changes in NFMs and changes in contemporaneous earnings diverge (H1):

$$\begin{aligned} GUIDANCE_{i,t} = {} & \beta_0 + \beta_1 ABS\_DIFF_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LN\_ANALYST_{i,t} \\ & + \beta_4 PRIOR\_FORECAST_{i,t} + \beta_5 LITIGATION_{i,t} + \beta_6 EQ\_ISS_{i,t} \\ & + \beta_7 DEBT\_FIN_{i,t} + \beta_8 PIH_{i,t} + \beta_9 DISPERSION_{i,t} + \beta_{10} CHG\_PPE_{i,t} \\ & + \beta_{11} R\&D_{i,t} + \beta_{12} LOSS_{i,t} + \beta_{13} XVOL_{i,t} + \beta_{14} ERC_{i,t} + e_{i,t} \end{aligned} \tag{2}$$

We apply a logit regression for Model (2) using the sample of 659 companies for which NFMs were collected and data were available to calculate variables in Model (2). For the companies which had available point or range management forecasts, we code *GUIDANCE* = 1 (N = 340), 0 otherwise. The focus for Model (2) is β_1. If the coefficient is positive, this suggests that managers are more compelled to issue guidance to provide clarity to investors when *ABS_DIFF* is larger. A negative coefficient is consistent with managers withholding guidance because NFMs are rendered a less valuable forecast input when *ABS_DIFF* is larger.

We follow the Hirst, Koonce, and Venkataraman (2008) framework and control for variables that influence the decision by managers to issue guidance. Firm size has been shown to be related to forecast bias (Ajinkya, Bhojraj, and Sengupta 2005) and disclosure frequency (Kasznik and Lev 1995). For this reason, we include *SIZE* as measured by the natural logarithm of the market value of equity at the end of year *t-1*. We include *LN_ANALYS*, measured as the natural log of the number of analysts following the firm in year *t*, to capture the uncertainty of

[17] While we rely upon *ABS_DIFF* in our primary analysis, we additionally examine if positive and negative (signed) *DIFF*s affects *GUIDANCE* differentially (see footnote 21).

the information environment and the difficulty of predicting earnings (Lang and Lundholm 1993; Cotter, 2006).

A pre-commitment to providing a management forecast is expected to reduce information asymmetry. Bhojraj, Libby, and Yang (2011) find that firms that commit to providing management forecasts have forecasts that are less optimistic, more accurate, and more precise. Choi, Myers, Zang, and Ziebart (2011) show that more frequent forecasting also improves investor responses to future earnings by improving forecast predictability. Accordingly, we include *PRIOR_FORECAST* measured as the number of years out of the past five years that the firm has provided a management forecast. To control for the threat of litigation associated with forecast bias, we include the variable *LITIGATION* to measure if the firm operates in a high litigation industry (Francis et al. 1994). Frankel, McNichols, and Wilson (1995) find a positive association between firms' decisions to access capital markets and to provide management forecasts. We include *EQ_ISS* and *DEBT_FIN* to capture the capital market incentives associated with disclosure.

Ajinkya et al. (2005) observe that institutional ownership is positively associated with the likelihood of releasing a management forecast. We thus control for the percentage of institutional ownership (*PIH*). To control for information asymmetry, we include the standard deviation of analyst forecasts (*DISPERSION*), calculated using the final consensus forecast for year *t*. We control for change in PP&E to proxy for growth opportunities. Consistent with Wang (2007), who finds that as proprietary costs (R&D expenditures) increase, managers release fewer forecasts, we include *R&D*. We include a control for current-year performance with the variable *LOSS* because managers are less likely to issue guidance when expecting future poor performance (Choi et al. 2011).

We control for two additional measures of financial performance that have been shown to influence the guidance decision – volatility of earnings and the earnings response coefficient (Choi et al. 2011). Earnings volatility (*XVOL*), measured as the volatility in earnings in the five years preceding year *t*, can increase ambiguity which may alter the guidance decision. Similarly, a smaller earnings response coefficient (*ERC*) may reflect poorer reporting transparency which may make issuing guidance more helpful. Last, while we are inclusive in terms of the industry coverage in our sample, the disclosure of NFMs will vary by industry. To avoid a few industries dominating our results, we include industry fixed effects in all models.

Forecast Accuracy (H2)

If NFMs and earnings are typically aligned, a larger *ABS_DIFF* likely renders NFMs as less diagnostic of contemporaneous earnings. Thus, while divergent patterns between NFMs and contemporaneous earnings may (or may not) provide incentives for management to issue guidance, such divergence should impair the accuracy of management forecasts. We employ the following model to test H2:

$$\begin{aligned} ABS\_MFE_{i,t} = {} & \gamma_0 + \gamma_1 ABS\_DIFF_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 ABEARN\_SURP_{i,t} \\ & + \gamma_4 LN\_ANALYS_{i,t} + \gamma_5 PRIOR\_FORECAST_{i,t} + \gamma_6\, LITIGATION_{i,t} \\ & + \gamma_7 EQ\_ISS_{i,t} + \gamma_8 DEBT\_FIN_{i,t} + \gamma_9 RET\_MKTADJ_{i,t} + \gamma_{10} BADNEWS_{i,t} \\ & + \gamma_{11} HORIZON_{i,t} + \gamma_{12} RANGE_{i,t} + e_{i,t} \end{aligned} \tag{3}$$

The absolute value of MFE (*ABS_MFE*) is used to examine the magnitude of error associated with *ABS_DIFF*. *ABS_MFE* is defined as the absolute value of the last management forecast for year *t* in year *t* less actual earnings per share for the year, scaled by price at the beginning of *t*.

H2 predicts that γ_1 will be positive.[18] We utilize many of the same control variables as described in Model (1) with a few additions. Controlling for information uncertainty, *ABEARN_SURP* is measured as the absolute value of the difference between the last management forecast in year *t* for year *t* and the consensus analysts' forecast for year *t*, scaled by price at the beginning of period *t.* McNichols (1989) and Rogers and Stocken (2005) find that management forecast errors are correlated with previous cumulative abnormal returns. For this reason, we include *RET_MKTADJ*.

We also include three control variables that account for forecast characteristics. *BADNEWS* is set equal to 1 if the management forecast is less than the consensus analyst forecast. Previous research suggests that forecasts conveying bad news are associated with analyst optimism, equity issuances, and litigation risk (Kasznik and Lev 2005). *BADNEWS* also addresses credibility concerns related to management forecasts (Ng, Tuna, and Verdi 2013; Merkley, Bamber, and Christensen 2012). To control for the forecast error associated with the forecast horizon documented by Rogers and Stocken (2005), we include *HORIZON*, measured as the number of days between the estimated earnings release date and the final management forecast issued by the firm. Last, *RANGE* is set equal to 1 if the management forecast includes both a low and a high earnings forecast and 0 otherwise. Table 2 provides definitions for all variables.

RESULTS

Descriptive Statistics

Table 3 provides descriptive statistics for our sample of firms that issued earnings guidance. For the 340 companies that issued management forecasts (51.6% of the total sample

[18] When discussing our results, we also examine if *ABS_DIFF* is associated with *signed* management forecast errors (more optimistic or pessimistic forecasts).

for which NFMs were collected), the average change in actual EPS (1.8%) is only slightly smaller than the average for *%MEDCHGNFM* (2.43%). In addition, the mean *DIFF* is –1.76%, which suggests that, on average, company changes in NFMs *are aligned* with actual earnings. A given rate of growth (*decline*) in NFMs is typically associated with an approximately equal rate of growth (*decline*) in contemporaneous earnings.[19] Further, the distribution of *DIFF* is not strongly skewed according to the 1st and 3rd quartiles of *DIFF* and as shown in Figure 1.[20] Because *ABS_DIFF* is not centered on zero, its mean is much larger than, but consistent with, the distribution of *DIFF*. For example, the median of *ABS_DIFF* (17.11%) is comparable to the 1st and 3rd quartiles of signed *DIFF* (–16.82% and 17.27%). For those firms that issue guidance, the absolute value of management forecast error in our sample (*ABS_MFE*) is 0.006. Finally, our control variable for historical forecast trends (*PRIOR_FORECAST*) shows that our forecasting companies issued forecasts, on average, in four of the five years leading into our sample period.

Results for H1 – Divergence and the Issuance of Guidance

We first examine whether the interplay between NFMs and contemporaneous earnings influences the decision to issue guidance (H1). We rely upon *ABS_DIFF* to measure the divergence between changes in NFMs and changes in earnings. Table 4 documents the results of our logit model for the decision to issue guidance. The 340 companies that issued forecasts are coded as *GUIDANCE* = 1. The remaining 319 companies in our sample that did not provide a forecast are coded as 0. We first note that the decision to issue forecasts in the past is a strong predictor of the decision to issue guidance in the future, as indicated by the significant positive result for *PRIOR_FORECAST*. Controlling for this past behavior is critical as we consider the impact of *ABS_DIFF* on the decision to issue guidance. The estimate for *ABS_DIFF* of –1.107

[19] A non-tabulated *t*-test confirms that the mean for *DIFF* of –1.76 is not significantly different from zero (*t*-stat = 1.02, p-value = 0.31).
[20] We winsorize all continuous variables at 1% to address extreme observations.

(*chi-square* of 22.57, p-value < 0.01) indicates that as the level of divergence between changes in NFMs and contemporaneous earnings increases, management is less likely to release a forecast.

As described in the development of H1, management is likely accustomed to using expected or observed changes in NFMs to forecast *similar* growth rates for earnings. Thus, in more divergent settings, management faces an atypical relation between a forecast input (NFMs) and what is being forecasted (earnings). Our H1 result suggests that this divergence, or the atypical presence of investment choices that are not recognized in the firm's earnings, causes management to not provide earnings guidance.

To further test this theory, it would be optimal to examine how previous years' divergence impacts the relation between *ABS_DIFF* and issuing guidance in the current-year. Specifically, if a firm's previous years' *ABS_DIFF*s are typically small, a large current-year *ABS_DIFF* should be *more atypical* and *more likely* to have a negative effect on *GUIDANCE*. However, we are limited in doing so by our hand-collected sample. Instead, to examine prior-year divergence levels, consistent with Brazel et al. (2009), we use the number of employees as our NFM due to its availability in prior-years (from Compustat). We calculate *ABS_DIFF_EMP* during the fiscal year *preceding* our sample period by using prior-year earnings and changes in employees and partition our sample into three groups based on *ABS_DIFF_EMP*: low, medium, and high. Using the partitioned samples, we separately examine Model (2) in the current-year for firms where *ABS_DIFF_EMP* is either low or high. Consistent with our theory, we find that the effect of *ABS_DIFF* on *GUIDANCE* in the current-year is stronger in cases where the company has experienced NFMs aligned with earnings in the past (i.e., when *ABS_DIFF_EMP* is low).[21]

[21] To further explore the nature of the divergence between NFMs and earnings, we consider signed *DIFF* in Model (2). A positive *DIFF*, where earnings performance outpaces NFMs, may be indicative of operational efficiencies as managers achieve higher earnings from less key inputs (i.e., NFMs). Negative *DIFF*, where NFMs outpace earnings performance, could allude to operational inefficiencies and/or a poor corporate strategy (e.g., excess

Results for H2 – Divergence and Forecast Accuracy

Our second hypothesis considers how the interplay between NFMs and contemporaneous earnings affects the accuracy of management forecasts (*ABS_MFE*). We first examine an unsigned measure of management forecast error because our initial focus is more on the magnitude of the error as opposed to the direction of the error. The first regression in Table 5 documents the result for Model (3), where we note that the relation between *ABS_DIFF* and *ABS_MFE* is positive and significant (*t*-stat 6.16, p-value < 0.01). The positive coefficient is consistent with our prediction in H2. When NFMs and contemporaneous earnings diverge, NFMs become less diagnostic of financial performance and management forecast accuracy suffers. Further, the reluctance of management to issue guidance in more divergent settings (our H1 result) appears justified. When management *does* issue guidance in more divergent settings, the accuracy of their forecasts is lower (as compared to managers forecasting under more aligned conditions). As noted previously, managers are concerned about their forecasting reputations (Graham et al. 2005), and they may face market penalties when releasing low quality forecasts (Dorantes et al. 2013).

In the second regression of Table 5, we apply *signed* management forecast errors to Model (3) to detect any directional forecasting bias. We find that when *ABS_DIFF* is larger, forecast errors are more likely to be optimistically biased based upon the positive and significant relation between *ABS_DIFF* and signed *MFE* (*t*-stat 4.67, p-value < 0.01). Not only can

capacity). To consider these possibilities and their relationship with *GUIDANCE*, we include an indicator variable for positive *DIFF* in Model (2) and also interact it with *ABS_DIFF* to re-perform our test of H1. In non-tabulated analyses, we find no pronounced effect for *ABS_DIFF* when *DIFF* is either positive or negative. Supplementing our full sample results from Table 4, we observe that divergence between NFMs and contemporaneous earnings in *either direction* deters management from issuing guidance.

managers less accurately predict earnings in the divergent setting, but, if they do issue guidance, they appear to do so with an optimistic bias.

A possible motivation for this positive bias is to encourage a corresponding upward revision of the market's future expectations for the company. To investigate this notion, we next examine management's revision of pre-existing expectations for earnings. While the previous result suggests that managers are overly optimistic when *ABS_DIFF* is larger, the optimism may not carry over when compared to existing benchmarks. Brown and Caylor (2005) demonstrate that current analysts' forecasts are a critical market expectation and managers may be motivated to encourage optimistic sentiments toward their company. On the other hand, over-enthusiasm that results in the company failing to achieve analysts' expectations can have negative market implications (Barth, Elloit, and Finn 1999). Therefore, we examine if *ABS_DIFF* influences whether managers use guidance to alter market expectations.

We compare management's last forecast in year *t* for year *t* to the consensus analysts' median forecast existing within the 30 days *preceding* management's forecast (*MF_REVISION*). Because we require an analyst's forecast within the preceding 30 days to calculate *MF_REVISION*, our sample size decreases to 285 companies (from 340). Table 6 provides the results for *MF_REVISION*. Consistent with the results pertaining to *MFE,* we find the coefficient for *ABS_DIFF* to be positive and significant, which is indicative of managers attempting to refine existing market expectations upward when greater divergence exists between changes in NFMs and earnings.

Precedence of Issuing Prior Forecasts

Our results in Table 4 related to H1 demonstrate that managers are less likely to issue forecasts when *ABS_DIFF* is greater. The results in Table 5 for H2 illustrate that when managers do issue forecasts in more divergent settings, managers are less accurate. These combined results raise the following question: given the difficulty in precisely forecasting earnings under divergent conditions, what motivates managers to issue a forecast when *ABS_DIFF* is high? Table 4 illustrates the strong impact prior forecasting has on *GUIDANCE*. One explanation may therefore be that the precedence of issuing prior forecasts makes it too costly for managers to stop providing guidance, even under more divergent conditions.

To address this issue more directly, we modify Model (2) and add an interaction term for *ABS_DIFF* and *PRIOR_FORECAST*. We examine if the relation between *ABS_DIFF* and the issuance of guidance is conditional on *PRIOR_FORECAST*. In non-tabulated analyses, we find that this interaction is not significant. Thus, a history of providing forecasts does not explain why some managers still provide guidance under divergent conditions. Alternatively, and perhaps more interestingly, this result does indicate that managers decide to *stop* issuing guidance when the divergence becomes larger, even when they have a history of providing guidance and the market likely expects an earnings forecast.[22]

ADDITIONAL ANALYSES

<u>Predicting</u> Forecasting Behavior

In our main analyses, we consider *contemporaneous* relations between management earnings forecast behavior, actual earnings, and NFMs. While our findings are helpful in explaining forecasting behavior, the timing of when NFMs are disclosed in the 10-K presents a challenge to external stakeholders (e.g., investors, creditors). Any divergence between financial measures and NFMs is typically exhibited when the company's 10-K is filed with the SEC after

[22] Another analysis to consider is whether, under more divergent conditions, managers are more likely to issue range versus point forecasts to minimize reputational costs. Unfortunately, our final sample resulted in only 15.6% of our sample issuing point forecasts (100% – *RANGE*) from Table 3. As a result, we lack the variability in our sample to examine this possibility.

year-end, likely several months *after* earnings forecasts are provided by management. As such, we conduct additional analyses to determine if observed divergences between financial measures and NFMs can be used by external stakeholders to *predict* future management forecasting behavior.

Related to the decision to issue a forecast, we repeat the analysis from Model (2) and Table 4 but measure *GUIDANCE* in year *t+1*. Table 7 provides the results for this analysis using the same set of 659 firms from Table 4 and finds that 282 companies issued guidance in year *t+1*. Consistent with our contemporaneous results, we observe that the effect of *ABS_DIFF* on *GUIDANCE* in year *t+1* is negative and significant. As the level of divergence increases, management is less likely to issue a forecast in the following year.

We also investigate the accuracy of future forecasts by modifying the forecast error in Model (3) to be the absolute forecast error (or signed forecast error) in period *t+1*. Table 8 provides the results for the 282 companies that issued forecasts in the subsequent year and demonstrates that *ABS_DIFF* is positively linked to future forecast errors. Overall, Tables 7 and 8 illustrate that external stakeholders can use the observed divergence between financial measures and NFMs as an early indicator of whether management will (1) issue forecasts next fiscal year, and (2) whether those forecasts will be accurate.

Testing of Assumptions

Our study builds on prior research that suggests that NFMs are typically aligned with actual earnings and are incorporated into management earnings forecasts (e.g., Baginski et al. 2004; Curtis et al. 2014). In Table 9, we empirically assess the validity of these assumptions. Related to the typical consistency between NFMs and earnings, we first demonstrate that the relation between our proxy for changes in NFMs (*%MEDCHGNFM*) and changes in *actual* contemporaneous earnings per share (*%CHANGE_EPS*) is significant and positive (first regression in Table 9). Consistent with prior studies (e.g., Brazel et al. 2009) and supporting the assumption used to develop our hypotheses, our results illustrate that changes in NFMs are both positively correlated and typically aligned with changes in contemporaneous earnings (also see Figure 1). Given the existence of this positive relation, NFMs should be a valuable input when managers develop earnings forecasts.

We examine two questions related to whether managers use their knowledge of NFM changes when developing their forecasts: (1) do managers incorporate *expected* changes in NFMs into their initial forecasts (*FIRST_ACTUAL)*, and (2) do managers incorporate *observed* changes in NFMs into their last forecasts (*LAST_ACTUAL)*? Turning to our two measures of management earnings forecast changes (second and third regressions in Table 9), we find the coefficient on %*MEDCHGNFM* to be positive and significant for both.[23] With *FIRST_ACTUAL*, the positive coefficient of 0.017 (*t*-stat of 1.97, p-value = 0.03) on %*MEDCHGNFM* suggests that management's forecasts of earnings early in the year are reflective of *planned* changes in NFMs. The results are even stronger when we examine *LAST_ACTUAL*. A forecasted change in earnings later in the year should contain the most information about *observed* changes in NFMs for the current-year. The coefficient of 0.027 (*t*-stat of 2.37, p-value = 0.01) is indicative of more informed managers understanding the implications of observed changes in NFMs during the year and using the information when developing their final forecasts.[24, 25] Combined, these results

[23] Because we examine NFM *changes*, we use forecasts of the earnings *changes*. For example, if actual earnings per share (EPS) for a company in the prior-year was $1.00 and the current-year management forecast of EPS is $1.25, then management's forecast of the earnings change for the current-year is $.25 or a 25% increase in EPS.

[24] In non-tabulated results, we observe that the coefficient for *%MEDCHGNFM* in the *LAST_ACTUAL* model is significantly greater than the coefficient for the *FIRST_ACTUAL* model (p-value = 0.08).

[25] We control for *%CHANGE_EPS* in Table 9 to test whether *%MEDCHGNFM* is simply a proxy/substitute for current year earnings or if *%MEDCHGNFM* contains additional explanatory power above *%CHANGE_EPS* in relation to forecasts. Our results suggest that NFMs are an important input for forecasting above and beyond contemporaneous, actual financial performance as measured by *%CHANGE_EPS*. Related to this notion, our tests

support our assumption that managers use expected changes in NFMs to provide guidance early in the year, as well as observed changes in NFMs when providing guidance later in the year.

CONCLUSION

This study examines the role of non-financial measures (NFMs) in management forecasting behavior. Building on the knowledge that NFMs are typically aligned with actual earnings and the premise that NFMs are likely incorporated into earnings forecasts, we investigate if the level of divergence between changes in NFMs and changes in contemporaneous earnings impacts management forecasting behavior.

We observe that as the level of divergence between changes in NFMs and changes in contemporaneous earnings increases, managers are less likely to issue forecasts. Management's hesitancy to issue guidance under divergent conditions appears warranted as those that do issue guidance in more divergent settings provide less accurate forecasts. We also find that the level of divergence is positively related to *signed* forecast errors and the extent to which management forecasts *exceed* the preceding consensus analyst forecast. These results indicate that when NFMs and contemporaneous earnings are not aligned, managers provide optimistic earnings guidance that is less accurate. Those who *use* management forecasts should be wary and perhaps discount forecasts issued under divergent conditions. Importantly, we also demonstrate that external stakeholders can use the level of divergence between NFMs and earnings to predict future management forecasting behavior. Overall, our evidence illustrates that NFMs and their relations with financial information play an important role in explaining management forecast behavior.

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of H1 and H2 examine how divergence between *%CHANGE_EPS and %MEDCHGNFM* affects forecasting behavior. Our results in Table 9 in relation to *%MEDCHGNFM* are robust to excluding *%CHANGE_EPS* from the analyses.

This study should spur future research related to NFMs and their relations with financial information. Our study uses annual disclosures of NFMs in 10-K filings with the SEC. Through our review of 10-Q filings, we observed that most companies do not provide NFMs or far fewer NFMs are reported in 10-Qs vs. 10-Ks. However, changes in NFMs (e.g., new store openings, patents, products, geographic expansion) are likely discussed by management in quarterly earnings conference calls, and researchers are now using advanced linguistic techniques to derive data and analyze these calls (e.g., Larcker and Zakolyukina 2012; Throckmorton, Mayew, Collins, and Venkatachalam 2015). It is possible that our measure of NFM/earnings divergence could be incorporated into linguistic analyses that assess the validity of the financial performance discussed during earnings calls. For example, prior research finds that that companies committing fraudulent financial reporting typically exhibit financial growth that is not supported by contemporaneous growth in NFMs (Brazel et al. 2009; Dechow et al. 2011). As such, future research could examine the calls of management that have committed fraud/experienced a financial statement restatement and determine if they are less likely to cite NFM changes when discussing financial performance (vs. a sample of non-fraud/restatement firms).

Our data collection efforts specifically focused on finding NFMs disclosed in both the current-year and prior-year for our sample of companies. Future research could examine the extent to which companies *change* the set of NFMs disclosed and what factors influence the set of NFMs reported to external users. Researchers could also consider the relative importance of earnings growth vis-à-vis NFM performance (e.g., user growth for a social media company) on firm value/stock price. Last, future studies could also investigate how divergence between financial data and related NFMs can be used to predict the future financial performance of companies. For example, current-year NFM growth that exceeds contemporaneous earnings growth may signal rising capacity at the company and, in turn, future earnings growth. Alternatively, such a pattern could predict over-capacity and future earnings declines.

The timing of our data collection coincided with substantial shocks to the economy (2007-2009). We made every effort to collect as much data as possible across all types of NFMs and various industries to normalize the economic impact as best we could. However, it is possible that the economic times within which our sample spans may have impacted our analyses. Future studies could investigate if the findings of our study generalize to more stable economic periods.

Appendix: Calculations of *%MEDCHGNFM*, *DIFF*, and *ABS_DIFF*

The formation of our sample requires the collection of capacity/performance-related NFMs disclosed in companies' 10-Ks. We collected the NFMs using a website developed for the Financial Industry Regulatory Authority. For each company in our sample, we use the median change in NFMs (*%MEDCHGNFM*) to proxy for the general direction of changes in company-specific NFMs. The calculation of *DIFF* then subtracts *%MEDCHGNFM* from the percentage change in earnings (*%CHANGE_EPS*). *ABS_DIFF*, our main variable of interest, is simply the absolute value of DIFF.

Taking a company from our sample, Verizon, below are the calculations for *%MEDCHGNFM, DIFF,* and *ABS_DIFF*.

Verizon

Financial Measure	**2007**	**2008**	**% Change**
Earnings (per share)	$2.36	$2.54	7.6%
Nonfinancial Measures – NFMs			
Broadband Connections	8,235,000	8,673,000	5.3%
Customers	65.7M	72.1M	9.7%
Countries Serviced	150	150	0.0%
Stores	2,400	2,500	4.2%
Wireline Access Lines	41M	36.161M	–11.8%
FiOS TV Customers	943,000	1,918,000	103.4%
IP Network (in miles)	485,000	485,000	0.0%
		%MEDCHGNFM	**4.2%**

DIFF **Calculation**:

%CHANGE_EPS – *%MEDCHGNFM* **=** ***DIFF***

7.6% – 4.2% **=** 3.4%

ABS_DIFF = |*DIFF*| = 3.4%

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Table 1: Panel A - Sample by Industry

Industry	# Companies	% Market Cap*
Personal services	84	46%
Retail	82	92%
Business equipment	60	39%
Healthcare	55	47%
Petroleum & natural gas	40	59%
Utilities	38	41%
Wholesale	38	79%
Restaurants, Hotels/Motels	29	52%
Transportation	23	56%
Fabricated products	21	52%
Food products	21	68%
Chemicals	20	56%
Communication	19	34%
Apparel	15	73%
Banking, Ins., Real Estate, Trading	14	5%
Consumer goods	13	26%
Electrical equipment	11	23%
Bus. supplies & shipping containers	11	33%
Printing & publishing	11	45%
Construction & materials	11	18%
Steel works etc	7	30%
Coal	7	97%
Recreation	6	34%
Aircraft, ships, railroad	6	39%
Beer & liquor	3	4%
Textiles	3	17%
Precious metals, Non-metal, mining	3	12%
Automobiles & trucks	2	68%
Tobacco	0	0%
Other	6	75%
	659	

* % of Market Cap is percentage of market capitalization collected relative to the total market capitalization for each industry (Fama-French 30-industry designation (Fama and French 1997) within Compustat for the sample period. We attempted to collect NFMs for no less than 90% of each industry. Failure to meet the criterion in any industry was the result of NFM collection issues documented in the text.

Table 1: Panel B - NFMs by Category

Category	Description	# NFMs in Sample
Employees	# employees (from Compustat)	659
Facilities (#)	# of major facilities owned or leased (centers, warehouses, stores, plants, buildings)	629
Products & Inventory	# brands or types of products/inventory; units sold or available for sale	410
Stores	# of stores, locations, and/or branches	403
Geographic Regions	# of large geographic areas, countries, states, and/or cities	393
Facility Size	square footage, miles, and/or acres of major facilities owned or leased (centers, warehouses, stores, plants, buildings)	356
Sales Channel	# of dealers and distributors from the company, capacity of sales channels, # revenue contracts and sales relations	310
Customers	# of customers, orders, visitors, clients; backlogs; metrics per customer	279
Patents & Trademarks	# patents and/or trademarks owned, acquired, developed, applied for	248
Suppliers	# of suppliers, manufacturers, and distributors to the company	51
Other^	Company-specific NFMs unique from those categories above	48
		3,786

^ "Other" represents collected NFMs that do not fit into one of the specific categories.

For each NFM above, we collected the NFM for the company for two consecutive years in order to measure changes in NFMs.

Table 1: Panel C - NFM Categories Disclosed by Industry

Industry	# NFM Categories
Consumer goods	10
Apparel	10
Healthcare	10
Fabricated products	10
Aircraft, ships, railroad	10
Petroleum & natural gas	10
Utilities	10
Personal services	10
Business equipment	10
Retail	10
Food products	9
Chemicals	9
Steel works etc	9
Communication	9
Bus. supplies & shipping containers	9
Transportation	9
Wholesale	9
Banking, Ins., Real Estate, Trading	9
Printing & publishing	8
Construction & materials	8
Electrical equipment	8
Restaurants, Hotels/Motels	8
Recreation	7
Textiles	7
Beer & liquor	6
Coal	6
Automobiles & trucks	5
Precious metals, Non-metal, mining	4
Tobacco	0
Other	8

This panel is a cross-section of our industry and NFM data from panels A and B, providing the number of NFM categories covered by companies within each industry. For example, in the Food Products industry, 9 of the 10 NFM categories have been disclosed by Food Product companies. This does not imply that every company in that industry has disclosed NFMs across 9 categories.

Table 2: Variable Definitions

Variable	Definition
%CHANGE_EPS	% change in actual earnings per share from I/B/E/S in year *t*.
%MEDCHGNFM	Median % change in non-financial measures for each company in year *t.*
DIFF (%)	Difference between %CHANGE_EPS and %MEDCHGNFM for each company in year *t.*
ABS_DIFF (%)	Absolute value of DIFF.
GUIDANCE	1 if the company issued an earnings forecast, 0 otherwise.
ABS_MFE	Absolute Difference between the last management forecast issued in year *t* for year *t* and EPS in year *t*, scaled by price at the beginning of year *t.*
MF_REVISION	Management Forecast Revision, calculated as the difference between the last management forecast in year *t* for year *t* and the pre-existing consensus analysts' median forecast taken within the 30 days preceding the management forecast.
FIRST_ACTUAL	Difference between the first management forecast issued in year *t* for year *t* and EPS in year *t-1*, scaled by price at the beginning of year *t.*
LAST_ACTUAL	Difference between the last management forecast issued in year *t* for year *t* and EPS in year *t-1*, scaled by price at the beginning of year *t.*
Control Variables:	
SIZE	Natural log of the market value of equity for year *t-1*.
ABEARN_SURP	Earnings Surprise, calculated as the absolute value of the difference between the last management forecast in year *t* for year *t* and the consensus analysts' forecast for year *t*, scaled by price at the beginning of period *t.*
LN_ANALYST	Natural log of the # of analysts following the company in year *t.*
PRIOR_FORECAST	# of years prior to year *t* (maximum of five) for which the company issued an annual EPS forecast.
LITIGATION	Litigation Risk, set equal to 1 when the company's industry is considered high risk per Francis et al. (1994a); 0 otherwise.
EQ_ISS	Cash provided by equity issuance scaled by total assets in year *t*.
DEBT_FIN	External Financing, set equal to 1 if the change in long-term debt is equal to or greater than 20%; 0 otherwise.
RET_MKTADJ	Market-adjusted Returns, calculated as the company's holding-period return for year *t* less the market return over the same year.
BADNEWS	Bad News, set equal to 1 when management forecast is less than the existing consensus analysts' forecast; 0 otherwise.
HORIZON	# days between the fiscal year-end (plus 45 days) and the last management forecast issued for year *t* in year *t.*
RANGE	Range of forecast issued, set equal to 1 if management provides both a low and high earnings forecast; 0 otherwise.
PIH	% of institutional holdings, % of shares outstanding held by institutional shareholders in year *t*.
DISPERSION	Analyst Dispersion, calculated as standard deviation of the last analysts' forecasts for year *t* in year *t.*
CHG_PPE	Change in PP&E, calculated as the percentage change in gross PP&E for year *t*.
R&D	R&D Expenditures, calculated as R&D costs scaled by total assets in year *t*.
LOSS	Operating Loss, set equal to 1 if operating income after depreciation is negative; 0 otherwise.
LCAPX	Lagged Capital Expenditures, measured as capital expenditures in t-1 scaled by total assets.
LPERF	Lagged Earnings Performance, measured as earnings per share in t-1.
LCONFORE	Lagged Consensus Analyst Forecast, taken from I/B/E/S in period t-1.
LEMP	Lagged # Employees, from period t-1 in thousands.
XVOL	Earnings Volatility, calculated as the standard deviation of earnings per share over the five years prior to year t.
ERC	Earnings Response Coefficient, measured as the coefficient on scaled earnings when annual returns are regressed on scaled earnings.

Table 3: Descriptive Statistics for Firms Issuing Guidance (N = 340)

Variables	Mean	Median	Standard Deviation	25%	75%
%CHANGE_EPS	1.8%	6.2%	37.1%	-13.0%	19.4%
%MEDCHGNFM	2.43%	0.74%	6.62%	0.00%	4.35%
DIFF (%)	−1.76%	1.63%	38.87%	−16.82%	17.27%
ABS_DIFF (%)	28.05%	17.11%	34.18%	8.11%	33.58%
ABS_MFE	0.006	0.002	0.009	0.001	0.007
MF_REVISION	−0.003	0.000	0.007	−0.002	0.001
Control Variables:					
SIZE	8.192	8.155	1.294	7.197	9.099
LN_ANALYST	2.563	2.565	0.538	2.197	2.944
PRIOR_FORECAST	4.14	5.00	1.347	4.000	5.000
LITIGATION	36.87%	0.00%	48.32%	0.00%	100%
EQ_ISS	0.007	0.004	0.010	0.001	0.009
DEBT_FIN	23.30%	0.00%	42.34%	0.00%	0.00%
PIH	75.06%	81.87%	25.99%	69.20%	92.05%
DISPERSION	0.004	0.002	0.005	0.001	0.005
CHG_PPE	7.51%	5.31%	10.43%	0.93%	11.78%
R&D	2.02%	0.00%	3.73%	0.00%	2.35%
LOSS	14.75%	0.00%	35.51%	0.00%	0.00%
XVOL	1.451	0.478	14.844	0.251	0.995
ERC	0.071	0.033	0.777	–0.085	0.153
ABEARN_SURP	0.003	0.002	0.003	0.000	0.004
RET_MKTADJ	4.51%	5.00%	23.72%	−13.70%	20.96%
BADNEWS	53.10%	100%	50.00%	0.00%	100%
HORIZON	127	107	76	96	121
RANGE	84.37%	100%	36.37%	100%	100%

See Table 2 for variable definitions. The full sample of 340 companies requires the availability of all above variables. Control variables are those used in our regression models (2) and (3).

Table 4: Manager's Decision to Issue Guidance

	Model (2) DV = GUIDANCE			
	Estimate	Chi-sq		Marginal Effect
Intercept	0.946	1.89		
ABS_DIFF	–1.107	22.57	***	0.389
SIZE	0.002	0.00		0.100
LN_ANALYST	0.065	0.08		0.252
PRIOR_FORECAST	1.149	18.21	***	2.607
LITIGATION	0.373	3.30	*	1.222
EQ_ISS	–1.555	3.30	*	1.201
DEBT_FIN	0.222	0.99		0.201
PIH	0.166	0.24		0.581
DISPERSION	0.154	0.21		0.050
CHG_PPE	–2.393	8.76	***	1.565
R&D	–3.196	1.84		0.480
LOSS	–0.689	8.81	***	1.924
XVOL	–0.307	7.61	***	0.948
ERC	–0.010	0.01		0.287
Likelihood Ratio	99.20 ***			
Total Observations	659			
# *GUIDANCE* = 1	340			
Industry effects	*YES*			

Our total number of observations (659) include those with required model variables. Three hundred and forty companies in that sample provided management forecasts We collected NFM data for the additional 319 companies that did not issue a management forecast during our sample period.

See Table 2 for variable definitions.

Model (2) logit model:

$$GUIDANCE_{i,t} = \beta_0 + \beta_1 ABS\_DIFF_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LN\_ANALYST_{i,t} + \beta_4 PRIOR\_FORECAST_{i,t} + \beta_5 LITIGATION_{i,t} + \beta_6 EQ\_ISS_{i,t} + \beta_7 DEBT\_FIN_{i,t} + \beta_8 PIH_{i,t} + \beta_9 DISPERSION_{i,t} + \beta_{10} CHG\_PPE_{i,t} + \beta_{11} R\&D_{i,t} + \beta_{12} LOSS_{i,t} + \beta_{13} XVOL_{i,t} + \beta_{14} ERC_{i,t} + e_{i,t}$$

*, **, *** denote significance at the 0.10, 0.05 and 0.01 levels, respectively; all p-values are two tailed.

Marginal effects are included to measure the incremental impact of a one unit change in the particular variable while holding all other variables constant at its respective mean.

Table 5: Management Forecast Error

	Model (3) DV = ABS_MFE			Model (3) DV = MFE		
	Coef.	***t-stat***		**Coef.**	***t-stat***	
Intercept	0.003	1.00		–0.001	–0.42	
ABS_DIFF	0.009	6.16	***	0.006	4.67	***
SIZE	–0.001	–1.05		0.000	0.57	
ABEARN_SURP	0.407	2.87	***	0.064	0.46	
LN_ANALYST	0.000	0.44		–0.001	–0.94	
PRIOR_FORECAST	0.000	0.96		–0.000	–0.79	
LITIGATION	0.002	1.64	*	–0.002	–1.73	*
EQ_ISS	–0.033	–0.69		–0.095	–2.06	**
DEBT_FIN	–0.001	–1.10		0.001	1.17	
RET_MKTADJ	–0.007	–3.44	***	–0.002	–1.05	
BADNEWS	0.000	0.39		–0.001	–1.34	
HORIZON	0.000	3.43	***	0.000	4.04	***
RANGE	–0.001	–0.53		0.000	0.04	
Adjusted R-square	28.43%			14.15%		
# Observations	340			340		
Industry effects	*YES*			*YES*		

See Table 2 for variable definitions. This table only includes the 340 companies for which we have management forecasts (vs. 659 in Table 1A).

Model (3) is used for both columns of results, only varying the dependent variable:

$$ABS\_MFE_{i,t} = \gamma_0 + \gamma_1 ABS\_DIFF_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 ABEARN\_SURP_{i,t} + \gamma_4 LN\_ANALYS_{i,t} + \gamma_5 PRIOR\_FORECAST_{i,t} + \gamma_6 LITIGATION_{i,t} + \gamma_7 EQ\_ISS_{i,t} + \gamma_8 DEBT\_FIN_{i,t} + \gamma_9 RET\_MKTADJ_{i,t} + \gamma_{10} BADNEWS_{i,t} + \gamma_{11} HORIZON_{i,t} + \gamma_{12} RANGE_{i,t} + e_{i,t}$$

*, **, *** denote significance at the 0.10, 0.05 and 0.01 levels, respectively; all p-values are two tailed except for *ABS_DIFF* where a directional prediction is made in our hypothesis in relation to *ABS_MFE* (one-tailed).

Table 6: Manager's Revision of Analysts' Forecasts

	DV = MF_REVISION		
	Coef.	***t-stat***	
Intercept	–0.001	–0.01	
ABS_DIFF	0.002	1.75	*
SIZE	–0.000	–0.63	
ABEARN_SURP	–0.599	–4.61	***
LN_ANALYS	0.001	1.31	
PRIOR_FORECAST	–0.000	–0.28	
LITIGATION	–0.001	–0.79	
EQ_ISS	0.025	0.58	
DEBT_FIN	–0.001	–0.58	
RET_MKTADJ	0.006	3.29	***
BADNEWS	–0.003	–3.77	***
HORIZON	0.000	1.99	**
RANGE	–0.000	–0.36	
Adjusted R-square	20.04%		
# Observations	285		
Industry effects	*YES*		

The reduction in sample size from 340 to 285 is necessary due to the requirement of a pre-existing consensus analyst forecast.

See Table 2 for variable definitions.

Model:

$$
\begin{aligned}
MF\_REVISION_{i,t} = {} & \gamma_0 + \gamma_1 ABS\_DIFF_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 ABEARN\_SURP_{i,t} \\
& + \gamma_4 LN\_ANALYS_{i,t} + \gamma_5 PRIOR\_FORECAST_{i,t} \\
& + \gamma_6\, LITIGATION_{i,t} + \gamma_7 EQ\_ISS_{i,t} + \gamma_8 DEBT\_FIN_{i,t} \\
& + \gamma_9 RET\_MKTADJ_{i,t} + \gamma_{10} BADNEWS_{i,t} + \gamma_{11} HORIZON_{i,t} \\
& + \gamma_{12} RANGE_{i,t} + e_{i,t}
\end{aligned}
$$

*, **, *** denote significance at the 0.10, 0.05 and 0.01 levels, respectively; all p-values are two tailed.

Table 7: Predicting Management's Decision to Issue Guidance

	Model (2) modified DV = GUIDANCE$_{t+1}$			
	Estimate	Chi-sq		Marginal Effect
Intercept	0.888	1.71		
ABS_DIFF	–1.213	23.24	***	0.297
SIZE	0.042	0.20		1.043
LN_ANALYS	–0.293	1.74		0.746
PRIOR_FORECAST	1.691	17.66	***	2.255
LITIGATION	0.206	1.04		1.229
EQ_ISS	–10.809	1.56		4.710
DEBT_FIN	0.294	1.85		1.342
PIH	0.260	0.57		1.297
DISPERSION	0.255	0.31		0.059
CHG_PPE	–1.606	3.94	**	0.201
R&D	–3.775	2.43		0.023
LOSS	–1.197	23.66	***	0.302
XVOL	–0.266	5.59	***	0.932
ERC	–0.011	0.02		0.279
Likelihood Ratio	97.36 ***			
Total Observations	659			
# *GUIDANCE* = 1	282			
Industry effects	*YES*			

We use the same observations from Table 5.

See Table 2 for variable definitions.

Model (3) logit model (modified):

$$GUIDANCE_{i,t+1} = \beta_0 + \beta_1 ABS\_DIFF_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LN\_ANALYST_{i,t} + \beta_4 PRIOR\_FORECAST_{i,t} + \beta_5 LITIGATION_{i,t} + \beta_6 EQ\_ISS_{i,t} + \beta_7 DEBT\_FIN_{i,t} + \beta_8 PIH_{i,t} + \beta_9 DISPERSION_{i,t} + \beta_{10} CHG\_PPE_{i,t} + \beta_{11} R\&D_{i,t} + \beta_{12} LOSS_{i,t} + \beta_{13} XVOL_{i,t} + \beta_{14} ERC_{i,t} + e_{i,t}$$

*, **, *** denote significance at the 0.10, 0.05 and 0.01 levels, respectively; all p-values are two tailed.

Marginal effects are included to measure the incremental impact of a one unit change in the particular variable while holding all other variables constant at its respective mean.

Table 8: Predicting Management Forecast Error

	Model (3) modified DV = ABS_MFE$_{t+1}$		Model (3) modified DV = MFE $_{t+1}$	
	Coef.	***t-stat***	**Coef.**	***t-stat***
Intercept	0.007	0.61	0.011	0.78
ABS_DIFF	0.031	5.87 ***	0.030	4.73 ***
SIZE	0.001	0.30	–0.004	–1.95 *
ABEARN_SURP	0.802	1.65	0.640	1.10
LN_ANALYS	–0.002	–0.61	0.005	1.06
PRIOR_FORECAST	0.000	0.89	–0.000	–0.58
LITIGATION	0.002	0.48	0.003	0.89
EQ_ISS	–0.173	–1.10	0.080	0.43
DEBT_FIN	–0.003	–1.10	–0.001	–0.11
RET_MKTADJ	–0.007	–1.05	0.018	2.27 **
BADNEWS	0.003	1.12	0.000	0.06
HORIZON	–0.001	–0.69	–0.001	–1.11
RANGE	0.002	0.53	–0.001	–0.27
Adjusted R-square	15.74%		11.96%	
# Observations	282		282	
Industry effects	*YES*		*YES*	

See Table 2 for variable definitions. This table only includes the 340 companies for which we have management forecasts (vs. 659 in Table 1A).

Model (3) modified is used for both columns of results, only changing the dependent variable:

$$ABS\_MFE_{i,t+1} = \gamma_0 + \gamma_1 ABS\_DIFF_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 ABEARN\_SURP_{i,t} + \gamma_4 LN\_ANALYS_{i,t} + \gamma_5 PRIOR\_FORECAST_{i,t} + \gamma_6 LITIGATION_{i,t} + \gamma_7 EQ\_ISS_{i,t} + \gamma_8 DEBT\_FIN_{i,t} + \gamma_9 RET\_MKTADJ_{i,t} + \gamma_{10} BADNEWS_{i,t} + \gamma_{11} HORIZON_{i,t} + \gamma_{12} RANGE_{i,t} + e_{i,t}$$

*, **, *** denote significance at the 0.10, 0.05 and 0.01 levels, respectively; all p-values are two tailed except for *ABS_DIFF* where a directional prediction is made in our hypothesis in relation to *ABS_MFE* (one-tailed).

Table 9: The Relation between NFMs and Management Forecasts

	DV = %CHANGE_EPS			DV = FIRST_ACTUAL			DV = LAST_ACTUAL		
	Coef.	***t-stat***		**Coef.**	***t-stat***		**Coef.**	***t-stat***	
Intercept	–0.255	–1.68		0.006	1.23		–0.004	–0.71	
%MEDCHGNFM	0.762	2.54	**	0.017	1.97	*	0.027	2.37	**
%CHANGE_EPS				0.015	9.54	***	0.023	10.75	***
SIZE	0.064	2.72	***	0.000	0.40		0.001	1.19	
ABEARN_SURP	–0.105	–1.52		–0.113	–0.63		–0.617	–2.62	**
LN_ANALYST	–0.086	–1.74		–0.001	–0.83		0.000	0.02	
PRIOR_FORECAST				–0.001	–0.56		–0.001	–1.09	
LITIGATION	–0.008	–0.18		–0.001	–0.98		–0.002	–1.53	
EQ_ISS	0.465	2.22	**	–0.082	–1.37		–0.125	–1.59	
DEBT_FIN	–0.060	–1.29		0.002	1.18		0.002	1.03	
RET_MKTADJ	0.231	2.69	***	–0.004	–1.51		0.006	1.84	*
BADNEWS				–0.001	–0.87		–0.004	–2.35	**
HORIZON				0.000	1.98		0.000	3.78	***
RANGE				0.001	0.19		–0.001	–0.48	
LCAPX	0.473	1.02		–0.024	–1.81		–0.020	–1.17	
LPERF	0.061	2.96	***	0.001	0.21		0.001	1.34	
LCONFORE	–0.089	–3.39	***	–0.001	–0.57		–0.003	–2.58	**
LEMP	–0.001	–0.56		0.001	0.57		0.000	0.10	
Adjusted R-square	13.02%			25.03%			40.04%		
# Observations	340			340			340		
Industry effects	*YES*			*YES*			*YES*		

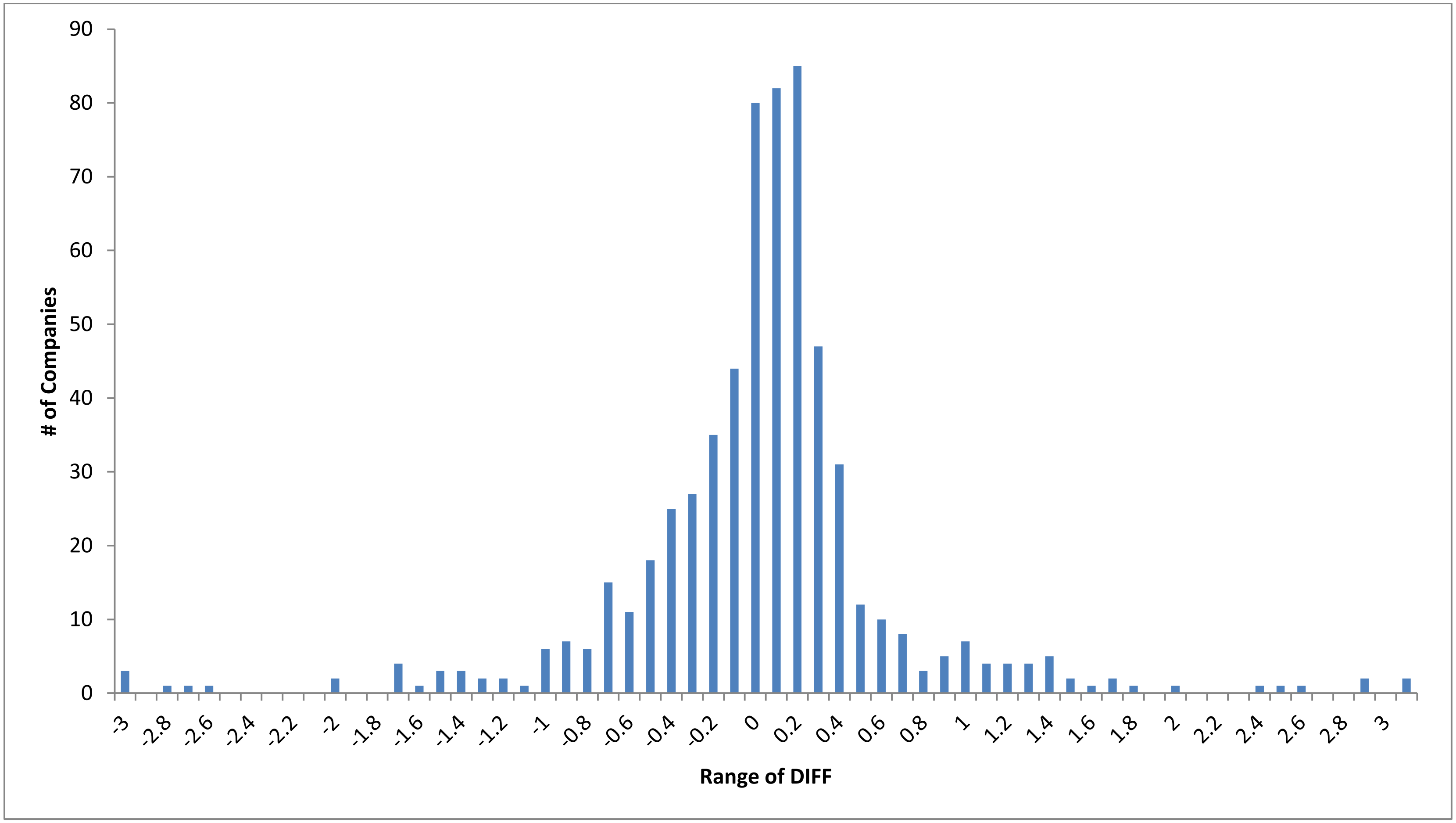
See Table 2 for variable definitions. This table only includes the 340 companies for which we have management forecasts (vs. 659 in Table 1, Panel A).
We use the following model:

$$MF_{i,t} = \gamma_0 + \gamma_1\%MEDCHGNFM_{i,t} + \gamma_2\%CHANGE\_EPS_{i,t} + \gamma_3 SIZE_{i,t} + \gamma_4 ABEARN\_SURP_{i,t} + \gamma_5 LN\_ANALYS_{i,t} + \gamma_6 PRIOR\_FORECAST_{i,t} + \gamma_7 LITIGATION_{i,t} + \gamma_8 EQ\_ISS_{i,t} + \gamma_9 DEBT\_FIN_{i,t} + \gamma_{10}\ RET\_MKTADJ_{i,t} + \gamma_{11} BADNEWS_{i,t} + \gamma_{12} HORIZON_{i,t} + \gamma_{13} RANGE_{i,t} + \gamma_{14} LCAPX_{i,t-1} + \gamma_{15} LPERF_{i,t-1} + \gamma_{16} LCONFORE_{i,t-1} + \gamma_{17} LEMP_{i,t-1} + e_{i,t}$$

MF_{it}, the dependent variable (DV), is measured in a different way for each column above (e.g., *%CHANGE_EPS*, *FIRST_ACTUAL*).

*, **, *** denote significance at the 0.10, 0.05 and 0.01 levels, respectively; all p-values are two-tailed.

Figure 1: Frequency Distribution of *DIFF*



DIFF (%) is calculated as the difference between *%CHANGE_EPS* and *%MEDCHGNFM* for each company in year *t* (see Table 2 for definitions). Positive *DIFF* (right side of the distribution) is indicative of changes in earnings outpacing contemporaneous changes in NFMs. A negative *DIFF* (left side of the distribution) is indicative of changes in NFMs outpacing contemporaneous changes in earnings.