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Fair value accounting and analyst forecast accuracy☆

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ABSTRACT

This study examines the effect of fair value accounting on the behavior of analysts using a large, generalizable sample of U.S. firms. By employing a measure of firms' fair value intensity, we provide evidence showing that firms with higher fair value intensity have more accurate analyst earnings forecasts, a significant main effect elusive to Magnan, Menini, and Parbonetti (2015). Furthermore, by using disclosures required by Statement of Financial Accounting Standards (SFAS) No. 157, we find significant positive associations between analyst forecast accuracy and Level 1 and Level 2 fair value measurements, but we do not find such association for Level 3 measurements. We document that these main effects are predominantly concentrated in non-financial industry firms in contrast to financial industry firms. This suggests that qualitative features of fair value measurements, including their business purpose and on-average accounting treatment (e.g., trading assets, available for sale, etc.), could also have an impact on analyst forecasting accuracy beyond mere measurement issues. Our results contribute to the debate over fair value accounting by showing the impact of fair value accounting upon an important participant in the capital markets.

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I. Introduction

We examine whether fair value measurements enhance analysts' forecasting accuracy.[1] Fair value measurements may augment forecasting, providing more timely data than historical cost measurements. However, such measurements may lack reliability and the presence of fair value items may increase the volatility of earnings, making the forecasting task more difficult. Prior studies have provided some evidence on the relationships between fair value measurements, firm value, and cost of capital, suggesting that these measurements are relevant to investors and creditors (Arora, Richardson, & Tuna, 2014; Song, Thomas, & Yi, 2010; Riedl & Serafeim, 2011; Goh, Li, Ng, & Ow Yong, 2015; Barth, 1994; Barth, Beaver, & Landsman, 1996; Barth, Hodder, & Stubben, 2008; Barth & Taylor, 2010; Barth, Ormazabal, & Taylor, 2012; Blankespoor, Linsmeier, Petroni, & Shakespeare, 2013; Graham, Lefanowicz, & Petroni, 2003; Carroll, Linsmeier, & Petroni, 2003; Venkatachalam, 1996). Yet, limited evidence exists on the relationship between fair value measurements and the accuracy of analyst earnings forecasts (see Magnan et al., 2015). We expand research in this area by examining the relationship between fair value measurements and analysts' information environment using a sample that includes financial and non-financial firms and comparing the relevance of these measurements in times of economic stability versus times of economic distress.

Developing a comprehensive understanding of the usefulness of fair value measurements is important as it can inform accounting standard setters and regulators on this issue. Over the past 25 years, the Financial Accounting Standards Board (FASB) has expanded the use of fair value measurements to include items such as derivatives and hedges, employee stock options, financial assets, and goodwill impairment testing. A significant standard in this area was Statement of Financial Accounting Standards (SFAS) No. 157, *Fair Value Measurements*. SFAS No. 157 established a framework of fair value measurement and required fair value measurements to be disclosed by levels (Level 1, 2, and 3), with Level 1 having the highest measurement certainty and Level 3 having the lowest level of measurement certainty Because Level 3 measurements inputs that are often not observable by investors, they are subject to greater estimation errors and biases, potentially causing them to be less reliable and create more severe information asymmetry between mangers and investors.[2]

Our study joins research streams that investigate both the usefulness of fair value measurements and the information used in the formation of analyst earnings forecasts. Analytical studies of analysts' behaviors provide models that illustrate the relation between information quality and

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[1] Analyst accuracy appears fairly consistent in seminal papers that analyze analyst forecasting abilities (Butler & Lang, 1991; Sinha, Brown, & Das, 1997; Clement, 1999; Mikhail, Walther, & Willis, 1997; Dhaliwal, Radhakrishnan, Tsang, & Yang, 2012). As a result, we primarily focus on analyst forecast accuracy in this study.

[2] Consistent with this intuition, prior literature (Petroni & Wahlen, 1995; Carroll et al., 2003; Song et al., 2010) documents that investors attribute more perceived value to Levels 1 and 2 fair value measurements than Level 3 fair value measurements.

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the characteristics of earnings forecasts (Diamond, 1985; Kim & Verrecchia, 1997; Barron, Kim, Lim, & Stevens, 1998). These studies suggest that more useful disclosures result in more accurate and less disperse earnings forecasts. Building upon these analytical models, empirical studies have employed the characteristics of analyst forecasts as a proxy for the quality of measurements (see, for example, Byard, Li, & Yu, 2011). We expand these studies by exploring the impact of fair value measurements across firms of different types under different economic conditions.

Fair value measurments may positively impact analysts' information environment as they provide timely and relevant information, which allows analysts to tether their expectations of earnings to overall movements in variables (e.g., macroeconomic variables such as interest rates) that affect the performance and pricing of assets, enhancing the analysts' ability to make accurate forecasts, as well as increasing consistency of forecasts across analysts. Analyzing text of conference calls and analysts' reports, Bischof, Daske, and Sextroh (2014) find that analysts devote a considerable amount of attention to fair value measurements. Furthermore, Bratten, Causholli, and Khan (2016) show that certain fair market measurements made by banks predict future financial performance. This finding provides some rationale for the interest in fair value measure among analysts found by Bischof et al. (2014). The Chartered Financial Analyst (CFA) Institute has been supportive of fair value accounting, arguing that it provides useful information to analysts (Magnan et al., 2015).

Alternatively, certain fair value measurements may cause increased volatility in earnings, enhanced opportunities for management discretion in financial reporting, and additional complexity to the forecasting process. Prior research has documented that the use of fair values measures increases the volatility of earning in banks (Barth, Landsman, & Wahlen, 1995). These issues associated with fair value accounting may lead to less accurate forecasts. In addition, incorporating fair value measurements into financial statements requires significant investment in systems used to capture, estimate, and record fair value disclosures (PwC, 2013[3]).

Our study contributes to the limited research examining the relationship between fair value measurements and analysts' forecasting outcomes. Recent research by Magnan et al. (2015) finds some early, but not conclusive, evidence on the relationship between fair value measurements and analyst forecasting. We build on this early evidence and provide a more comprehensive analysis of the relationship between analysts' forecast accuracy and fair value measurements. Our study contributes to this line of research by examining the impact of fair value measurements on analysts' forecast accuracies using a broader sample of firms and a broader range of years following the financial crisis.[4] Both financial and non-financial firms commonly employ different levels and types of assets and liabilities subject to fair value accounting standards. We believe that the examination of non-banks results in a more generalizable analysis and permits us to focus more extensively on the levels of disclosures as defined in SFAS No. 157.

In addition to using a broader sample of firms, we extend Magnan et al. (2015) by examining the impact of fair value measurements on analysts' forecasting in times of economic stability and growth versus times of economic instability.[5] Many would argue that fair value measurements are most useful in volatile economic times when the correlation between historical cost and fair market value may decline. The 2007–2009 financial crisis reignited vigorous debate regarding fair value accounting among standard setters, regulators, politicians, academics, and the general business community.[6] Proponents of fair value accounting (comment letters by the Center for Audit quality, the CFA Institute, the Council of Institutional Investors, and the Consumer Federation of America, 2008[7]) argue that it provides more timely and value-relevant information to market participants than do other alternative accounting approaches (i.e., historical cost accounting). In contrast, opponents argue that fair value accounting has made companies' financial information less reliable and less comparable. For example, William Isaac, a former Chairman of the Federal Deposit Insurance Corporation (FDIC), when speaking about fair value accounting, said, "There is nothing fair about a system that is transparently wrong. It has been senselessly destructive of bank capital."[8] During and after the peak of the financial crisis in 2008, the Securities and Exchange Commission (SEC) was urged by many prominent figures in finance and politics to suspend fair value accounting.[9] Recent academic research provides conflicting evidence on the impact of fair value measurements on the financial crisis (Barth & Landsman, 2010; De Jager, 2014). Given this lack of consensus among academics and market participants on the usefulness of fair value disclosures during the financial crisis, we believe that a better understanding of the relevance of fair value measurements under different economic conditions has meaningful policy implications.

Our analysis employs a large, generalizable sample of firm-years from all industries between 2007 and 2013. In the first series of tests, we examine the relation between aggregate fair market measurements and the analysts' forecast accuracy. By using the proportion of fair value assets and liabilities to total assets as our measure of fair value intensity, we find a significant positive association between fair value intensity and analysts' forecast accuracies after controlling for other firm characteristics that affect analyst forecasts. Specifically, forecast accuracy is increased with more extensive fair value measurements. This main effect was elusive to Magnan et al. (2015). This finding initially suggests that fair value accounting enhances analysts' forecasting abilities.

In the second series of tests, we investigate whether SFAS No. 157 fair value measurements (i.e., Levels 1, 2, and 3) have differential impacts upon forecast outcomes. Interestingly, we find significant positive associations between analyst forecast accuracy and Levels 1 and 2 measurements, while we find no evidence of a relation for Level 3 measurements. These results differ significantly from those of Magnan et al. (2015), as they only find an effect with Level 2 measurements. These results initially suggest that the more reliable Levels 1 and 2 measurements enhance the accuracy of analysts' forecasts.

We further bifurcate our sample and tests between financial industry and non-financial industry firms. Our results suggest that the predominant drivers of our results for analyst accuracy are non-financial industry firms. We posit that these findings may be driven by qualitative differences in the accounting treatment, use, or purposes of these measurements between financial and non-financial industries. We find anecdotal evidence that financial industry firms are more likely to classify their fair value measurements as trading assets, which, in theory, would induce further volatility in operating earnings. Differences in accounting treatment by the two large industry groupings likely result in differing levels of inherent complexity around the forecasting task of analysts.

We further find that the financial crisis had a dramatic impact on fair value measurements upon forecast accuracy for financial industry firms, a notion suggested by Magnan et al. (2015). Specifically using our sample of financial firms, we find that fair value measurements are

[3] https://www.pwc.com/us/en/tax-accounting-services/newsletters/tax-accounting/assets/pwc-fair-value-accounting-march-2013.pdf.

[4] Magnan et al. (2015) examine the relationship between fair value disclosures of banks (as required by the FR Y-9C) and analyst earnings forecasts. No significant main effect regarding the impact of fair value measurements upon forecast accuracy was identified in the main analysis, but they do find that the relation changed with the advent of SFAS No. 157 in 2007.

[5] Magnan et al.'s (2015) sample ends in 2009, at the height of the financial crisis.

[6] Forbes "The Great Fair-Value Debate" http://www.forbes.com/2009/08/19/mark-market-accounting-leadership-governance-directorship.html; Harvard Business Review, "Is it fair to blame fair value accounting for the financial crisis?" https://hbr.org/2009/11/is-it-fair-to-blame-fair-value-accounting-for-the-financial-crisis; etc.

[7] Joint comment letter on fair value: http://thecaq.org/policy/fair-value-accounting.

[8] Transcript of Mark to Market Accounting Roundtable https://www.sec.gov/spotlight/fairvalue/marktomarket/mtmtranscript102908.pdf.

[9] Transcript of Mark to Market Accounting Roundtable https://www.sec.gov/spotlight/fairvalue/marktomarket/mtmtranscript102908.pdf.

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positively (negatively) related to forecast accuracy during the financial crisis (non-financial crisis) period. Our results for the financial industry sample during the financial crisis thus mirror those of Magnan et al. (2015), but diverge thereafter. For our sample of non-financial firms, we find that fair value measurements are positively related to accuracy in the years of crisis and the years following the crisis. Magnan et al. (2015) attribute their results to an enhanced information environment that was brought about by the inception of SFAS No. 157. Our results cast some doubt upon this notion and potentially provide an avenue for future research within this important aspect of accounting.

This study makes several contributions. First, at the most fundamental level, our study provides direct evidence of how fair value accounting affects analysts' forecast accuracies. Prior literature has primarily focused on how fair value accounting is impounded into security prices (Barth, 1994; Barth et al., 1996; Eccher, Ramesh, & Thiagarajan, 1996; Carroll et al., 2003; Song et al., 2010). As addressed in Holthausen and Watts (2001), empirical evidence on the relation between accounting information and stock prices says very little about whether the information affects users, and our results are suggestive that fair value accounting, on average, improves the abilities of financial analysts.

The second contribution of our paper is that we address the SFAS No. 157 fair value hierarchy within an analyst context. Song et al. (2010) find that value relevance is greater for Levels 1 and 2 measurements than Level 3 measurements. Riedl and Serafeim (2011) similarly document that Level 3 measurements are associated with a higher cost of capital than Levels 1 and 2 measurements. Our findings (i.e., analyst forecasts are improved by Levels 1 and 2 measurements) further support previous findings that attribute higher value relevance to Levels 1 and 2 measurements. This finding contributes to the fair value hierarchy literature. We also provide new evidence on the relevance of fair value measurements across financial and non-financial firms, in times of economic stability and distress. These differences are found to affect the impact of these measurements on analysts' information environment.

The rest of the paper is organized as follows. In the next section, we discuss our motivation and hypotheses development. Section III presents our research design and sample selection. Section IV provides descriptive data and discusses our main empirical analysis. Section V concludes.

II. Background and hypotheses

a. Fair value accounting

After the savings and loan crisis of the 1980s, the use of historical cost accounting in the banking system was harshly criticized for not providing timely and relevant information. Many believe that fair value accounting would have led financial statement users to address these institutions' financial difficulties earlier and thus reduce the cost of the financial failures. Fair value accounting was then portrayed as and advocated for in the belief that it reflects underlying economic substance more closely with reality. This advocacy was echoed by former SEC Chairman Breeden, who stated that "market value-based information is the most relevant financial information during his testimony in front of the Committee on Banking, Housing, and Urban Affairs of the U.S. Senate." During the past two decades, accounting standards have thus been moving toward greater use of fair value accounting. However, opponents of fair value accounting argue that it is more subjective and therefore less reliable. This criticism was magnified after the financial crisis of 2007–2009.

Prior research on the relevance of fair value accounting has reported mixed findings (Barth, 1994). Some studies show that historical cost earnings dominate other alternative cost measures (Beaver, Griffin, & Landsman, 1982; Beaver & Landsman, 1983; Beaver & Ryan, 1985; Bernard & Ruland, 1987). However, other studies (Bublitz, Frecka, & McKeown, 1985; Murdoch, 1986; Haw & Lustgarten, 1988; Barth et al., 1996; Eccher et al., 1996; Song et al., 2010) find that fair value measurements have incremental explanatory power beyond historical cost accounting. An additional line of research, using indirect inferences from stock prices, suggests that investors use fair value accounting in their firm-valuation decision-making (Barth, 1994; Barth et al., 1996; Eccher et al., 1996; Carroll et al., 2003) – fair value measurements are more readily impounded in security prices than historical cost measurements. Also, fair value measurements appear to have an impact on not only investors' decision-making, but also auditors' decision-making processes (Ettredge, Xu, & Yi, 2014).

Prior studies have examined the reliability of fair value measurements. For example, Petroni and Wahlen (1995) and Carroll et al. (2003) show that investors respond more strongly to fair value measurements of assets that are traded in deeply liquid markets than those that are traded in non-liquid markets. This suggests that investors perceive different levels of reliability for different types of fair value assets. Other studies find evidence that managers apply considerable discretions in their fair value estimates, but external monitoring reduces their behavior (Deitrich, Harris, & Muller, 2000; Muller & Riedl, 2002; Dechow, Myers, & Shakespeare, 2008; Jung, Pourjalali, Wen, & Daniel, 2013; Lee & Park, 2013).

Our study adds to this literature by examining an alternative proxy for the usefulness of fair value measurements–their impact on financial analysts. We attempt to provide validation of these market-based studies by showing that fair value measurements are not only informative to investors, but also improve financial analysts' information environments. Such consistency can help alleviate some concerns, such as the reliance of empirical evidence on the relation between accounting information and stock prices expressed by Holthausen and Watts (2001).

b. Prior research on analyst earnings forecasts

Analysts are sophisticated financial statement users who aggregate both financial and non-financial information to derive earnings estimates (Schipper, 1991). There has been extensive interest in the accounting literature investigating analysts' actual decision processes. Analysts gather firm-specific, industry-specific, and economy-wide information to generate earnings forecasts. Properties of these earnings forecasts (e.g., forecast accuracy and dispersion) have been commonly used to infer attributes of information used to generate the earnings forecast. Prior studies document that analyst forecast accuracy increases with the availability of new information (Waymire, 1986; Kross, Ro, & Schroeder, 1990; Bowen, Davis, & Matsumoto, 2002; Hope, 2003a, 2003b; Baginski, Hassell, & Wieland, 2011; Dhaliwal et al., 2012), the informativeness of information (Lang & Lundholm, 1996; Barron et al., 1998; Lehavy, Li, & Merkley, 2011), and the reliability of information (Behn, Choi, & Kang, 2008). Furthermore, previous research also shows that analyst forecast accuracy decreases with increases to the difficulty level of the forecasting task. For example, analyst forecast accuracy is negatively affected by goodwill impairment charges (Chen, Krishnan, & Sami, 2015), a high level of intangible assets (Barron, Byard, Kile, & Riedl, 2002), restructuring charges (Chaney, Hogan, & Jeter, 1999), international diversification (Duru & Reeb, 2002), complexities of tax laws (Plumlee, 2003), low-quality MD&A (Barron et al., 1998), and less readable 10-Ks (Lehavy et al., 2011). Other studies have found that the idiosyncratic traits of analysts, such as experience and specialization, also affect forecasting outcomes (Jacob, Lys, & Neale, 1999; Clement, 1999). We add to this line of literature by examining the impact of fair value measurements on analysts' forecasting outcomes. Specifically, our study provides evidence on whether or not fair value measurements are associated with more accurate forecasts.

c. The effects of fair value accounting on analyst earnings forecasts

Our paper links two streams of contemporary research: fair value measurements and analyst forecasts. Although there is substantial research on analyst forecast properties, few studies examine how analysts respond to fair value measurements. Using an experimental design, Hirst, Hopkins, and Wahlen (2004) demonstrate that different income measurements (full-fair-value versus piecemeal-fair-value) affect analysts' risk and valuation judgments differently. We add to this study by examining the effect of fair value measurements on properties of earnings forecasts.

Using a sample of property investment firms from the U.K. and U.S., Liang and Riedl (2014) examine the relation between fair value measurements and both balance sheet- and income statement- based forecasts. The authors document that fair value measurements of real estate enhance analysts' abilities to make accurate balance sheet forecasts but not income statement forecasts. We differ from Liang and Riedl (2014) in many ways. First, we use a domestic sample of firms, which better controls for international differences in accounting standards, regulation, and enforcement, all of which may impact analyst activity (Barniv, Myring, & Thomas, 2005). Furthermore, we partition fair value measurements based on SFAS No. 157 and examine the relation between Levels 1, 2, and 3 measurements and analysts' forecast properties, while Liang and Riedl (2014) focus on only relatively subjective fair value measurements of investment property.

Using a sample of US bank holding companies from 1996 to 2009, Magnan et al. (2015) examine whether or not and how fair value measurements affect analysts' earnings forecasting abilities. The authors find that the advent of SFAS No. 157 ameliorates analyst forecast dispersion while improving accuracy. Our paper is different from Magnan et al. (2015) in the following ways. First, we use a longer period after the adoption of SFAS No. 157, trying to find whether the effects of SFAS No. 157 hold even after the financial crisis period. For Magnan et al. (2015), the financial crisis period of 2007–2009 represents a significant confound to their study, especially since most of the results of interest are driven by this unique period. We also explore a much more generalizable sample of firm years, and our sample is not limited to bank holding companies alone. By structuring our paper in this manner, we hope to provide more clarity to the effects of fair value measurements upon forecasting outcomes.

d. Hypotheses development

Our first hypothesis examines the relationship between fair-value measurements and analyst earnings forecast accuracy. If fair value measurements increase the overall quality of financial disclosures available to analysts, such measurements may improve analyst forecast accuracy. Empirical research suggests that fair value measurements are relevant to investors, implying that they enhance the quality of financial statement content. Specifically, capital market research shows that the fair values of banks' derivatives, trading, and investment securities have incremental value relevance than amortized cost and this value relevance is a function of the reliability of the fair value measurements (Barth et al., 1996; Eccher et al., 1996; Graham et al., 2003; Ahmed, Kilic, & Lobo, 2006). In addition, experimental studies show that fair value information is perceived to be useful by users under certain circumstances (Hirst et al., 2004; Koonce, Nelson, & Shakespeare, 2011).

Evidence from practice suggests that sophisticated users of financial statements recognize the importance of fair value measurements. In 2005, the CFA Institute proposed 12 principles to strengthen the transparency, clarity, and comprehensive disclosures of financial statements. Principle 2 states, "Fair value information is the only information relevant for financial decision making" (A Comprehensive Business Reporting Model: Financial Reporting for Investors 2005 – CFA Institute) because it provides the most current and relevant information to help investors make well-informed decisions. Empirical research is consistent with the calls of the CFA Institute regarding the usefulness of fair value measurements. Using a unique data set of banks' (using IFRS) conference call transcripts, Bischof et al. (2014) show that analysts frequently ask questions about fair value-related measurements.[10]

On the other hand, it is possible that the presence of assets and liabilities subject to fair value measurement may decrease analyst forecast accuracy. Firms that have extensive fair value measurements may have more complex business models, making the forecasting exercise more complex. Specifically, prior literature provides evidence showing that analyst forecast accuracy is adversely affected when the forecasting task is difficult (Barron et al., 2002; Chen et al., 2015). Also, certain fair value measurements may also increase the volatility of earnings, making the task of forecasting earnings even more challenging.

In addition to the increased complexity of forecasting earnings in the presence of assets subject to valuation, there is some evidence of a decline in analyst information quality following the adoption of SFAS No. 157. Using the measures of private and common information quality developed by Barron et al. (1998), Li (2014) finds that analysts' information qualities decrease following the adoption of SFAS No.157. Furthermore, certain measurements qualify for different accounting treatments (e.g., trading assets, available for sale assets, etc.) which ultimately affect earnings and potentially confound the earnings forecasting process. These items suggest that fair value measurement may result in less accurate analyst forecasts.

As we cannot predict the relative strength of these offsetting effects on fair value, it is not clear how fair value measurements will impact analyst earnings forecasts. This leads to the first hypothesis:

H1. Analyst forecast accuracy is unrelated to fair value intensity.

Our second hypothesis examines the relation between the type of fair value measurement and the accuracy of analysts' forecasts. SFAS No. 157 provides a coherent framework for applying fair value measurements and prioritizes the classification of fair value assets and liabilities into three levels: Levels 1 and 2 inputs are either directly or indirectly observable, and Level 3 inputs are unobservable. This fair value hierarchy suggests that fair value measurements have substantial differences in measurement and reliability. Within this framework, Level 3 fair values are less observable and are subject to greater estimation and uncertainty.

Consistent with this intuition, Song et al. (2010) find that value relevance is greater for Levels 1 and 2 fair value measurements than for Level 3 fair value measurements. Also, Riedl and Serafeim (2011) find that Level 3 fair value measurements result in higher costs of capital than Levels 1 and 2 measurements. Ettredge et al. (2014) further document that audit fees are positively associated with fair value intensity and that this positive relationship is stronger for Level 3 fair value measurements. This finding signals that auditors either are exposed to more risk with these types of measurements or need to expend more efforts in mitigating the risk presented by these measurements. Overall, the lack of observability and higher subjectivity of Level 3 fair value measurements pose estimation hurdles for analysts as they produce forecasts.

Since the issuance of SFAS No. 157, the FASB has expanded the disclosure requirements related to Level 3 items. Specifically, Fair Value Measurement (Topic 820), issued in 2011, expanded the disclosures for Level 3 measurements. Specifically, this enhancement required the valuation processes used by the reporting entity and the sensitivity of the fair value measurement to changes in unobservable inputs and the

[10] Using all of the conference call transcripts of IFRS banks from January 1, 2008, to December 31, 2010, Bischof et al. (2014) find that analysts ask questions about fair value-related information in 15.8% of all of the conference calls in their sample (130 of 824 calls). Their analysis also provides evidence on circumstances under which analysts demand more fair value-related information.

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interrelationships between those unobservable inputs to be disclosed.[11] While these enhanced disclosures requirements are reflective of the difficulty financial statement users have interpreting this complex information, they also may represent an improvement in the accuracy of analyst's forecasts.

On the contrary, Level 3 measurements, since they have a higher level of subjectivity in their valuation, may be less volatile than are Levels 1 and 2 measurements. This increased subjectivity could even provide management with opportunities to manage earnings to predetermined analyst forecasts, artificially enhancing their impact on forecast accuracy. As a result, a significant amount of tension exists between the impact of Levels 1 and 2 measurements versus Level 3 measurements.

H2. Ceteris paribus, Levels 1 and 2 measurements do not have a different impact on forecast accuracy from those of Level 3 measurements.

III. Research design and sample selection

a. Research design

To explore the relation between fair value measurements and analyst forecast accuracy, this paper employs the following pooled cross-sectional models using ordinary least squares[12]:

$$\begin{aligned} ACCURACY_{it} &= \lambda_0 + \lambda_1 FV\_INTENSITY_{it} + \lambda_2 SIZE_t + \lambda_3 LOSS_{it} + \lambda_4 EARN\_VOLATILITY_{it} \\ &+ \lambda_5 LEVERAGE_{it} + \lambda_6 MKTBK_{it} + \lambda_7 SEGMENTS_{it} + \lambda_8 EARN\_MOMENTUM_{it} \\ &+ \lambda_9 FOLLOWING_{it} + \sum INDUSTRY_{it} + \sum YEAR_{it} + \mu_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} ACCURACY_{it} &= \beta_0 + \beta_1 LVL\_ONE\_INTENSITY_{it} + \beta_2 LVL\_TWO\_INTENSITY_{it} \\ &+ \beta_3 LVL\_THREE\_INTENSITY_{it} + \beta_4 SIZE_t + \beta_5 LOSS_{it} + \beta_6 EARN\_VOLATILITY_{it} \\ &+ \beta_7 LEVERAGE_{it} + \beta_8 MKTBK_{it} + \beta_9 SEGMENTS_{it} + \beta_{10} EARN\_MOMENTUM_{it} \\ &+ \beta_{11} FOLLOWING_{it} + \sum INDUSTRY_{it} + \sum YEAR_{it} + \mu_{it} \end{aligned} \tag{2}$$

ACCURACY, the proxy for forecast accuracy, is similar to measures used in prior research (Lang & Lundholm, 1996; Mikhail et al., 1997; Hong & Kubik, 2003; Duru & Reeb, 2002; Chen et al., 2015). It is computed as negative one times the absolute value of the difference between actual earnings and the consensus analyst forecast, deflated by year-end stock price.[13] Since *ACCURACY* involves the calculation of a ratio, it is prone to statistical outliers in its formulation.[14] As a result, *ACCURACY* has been winsorized at the 2% and 98% levels to reduce the impact of such outliers. All other continuous variables have also been winsorized at the 1% and 99% levels to reduce the impact of outliers. The Appendix A contains detailed variable descriptions.

Eq. (1) is used to test Hypothesis 1 as it employs *FV_INTENSITY* (total fair value assets and liabilities divided by total assets) as a measure of overall fair value asset holdings. This measurement is similar to the one employed by Magnan et al. (2015). In robustness tests, we also employ an alternative specification (total fair value assets alone scaled by total assets), similar to Ettredge et al. (2014), as an alternative measure of a firm's exposure to fair value accounting in lieu of *FV_ASSETS*.

Eq. (2) is used to test Hypothesis 2 as it employs more nuanced measures of fair value asset holdings using the SFAS No. 157 level measurements [*LVL_ONE_INTENSITY* (Level 1 assets and liabilities divided by total assets), *LVL_TWO_INTENSITY* (Level 2 assets and liabilities divided by total assets), and *LVL_THREE_INTENSITY* (Level 3 assets and liabilities divided by total assets)] for measurement. These measurements follow Riedl and Serafeim (2011). In robustness tests, we also employ the alternative measures for Level 1 measurements (Level 1 assets scaled by total assets), Level 2 measurements (Level 2 assets scaled by total assets), and Level 3 measurements (level three assets scaled by total assets) in lieu of *LVL_ONE_INTENSITY*, *LVL_TWO_INTENSITY*, and *LVL_THREE_INTENSITY* within our regression specifications.[15] Positive coefficients for all of these measurements would signal that the respective measures of fair accounting intensity are associated with higher forecast accuracy. Negative coefficients would signal that the measures are associated with reduced accuracy.

SIZE is used to control for the size of firm *i* and is calculated using the natural log of total assets. Firm size has been found to have an impact on forecast accuracy (Chen et al., 2015; Lehavy et al., 2011). *LOSS* is an indicator variable equal to one if the firm had negative net income for the year and follows prior research (Duru & Reeb, 2002). Given that losses typically occur in heightened times of uncertainty or distress, we expect *LOSS* to be associated with lower forecast accuracy.

EARN_VOLATILITY is used to proxy for the historical variability in earnings of the firm (Duru & Reeb, 2002). Ceteris paribus, the higher the historical volatility is in earnings, the higher the difficulty is in predicting current period earnings. Thus, we anticipate that *EARN_VOLATILITY* will be associated with lower forecast accuracy. *EARN_VOLATILITY* is measured using the standard deviation of firm *i*'s return on assets for the previous five years.

LEVERAGE is employed to proxy for firm *i*'s exposure to financial leverage. Financial leverage can induce higher levels of earnings volatility by increasing financial risk, given all things are equal (Parkash, Dhaliwal, & Salatka, 1995). As a result, we expect exposure to financial leverage to reduce forecast accuracy. *LEVERAGE* is measured using the ratio of interest-bearing debt to total assets.

MKTBK is used to measure both a firm's growth prospects and its holdings of growth assets. This variable is computed as the ratio of the market value of assets (market value of equity plus the book value of liabilities) divided by the book value of assets. Firms with higher growth prospects are likely to have different forecasting outcomes than firms with lower growth prospects. In a similar vein and following Duru and Reeb (2002), we also employ *EARN_MOMENTUM*, the change in earnings from one period to the next, scaled by lagged price. *SEGMENTS* is used to proxy for firm complexity and is the number of operating segments for firm *i*.

Finally, we also employ *FOLLOWING* to capture the overall oversight of firm *i* by the analyst community. Higher levels of analyst following have been found to have an impact of forecasting outcomes (Hong & Kacperczyk, 2010). As a result, we expect higher levels of analyst following to improve forecast accuracy. This variable is measured using the

[11] Most recently, in December 2015, the board issued another Exposure Draft intended to update Fair Value Measurement (Topic 820). The goal of this exposure draft was to make financial statement disclosures more effective, balancing the information demand of the users with the costs and complexity of producing that information. Consistent with this overall objective, this exposure draft proposed significant cuts of current disclosure for Levels 1 and 2 measurements. However, at the same time, the board proposed adding disclosures for Level 3 measurements. For example, the range, weighted average, and period used to develop significant unobservable inputs for Level 3 were proposed to be disclosed.

[12] To reduce the effect of any correlation in the error term at the firm level, robust standard errors are computed and clustered at the firm level. To the extent that any correlation exists along the time dimension of our panel, this is controlled for parametrically though the use of time period dummy variables (Petersen, 2009).

[13] In robustness testing, we employ several alternative measures of this construct using the absolute value of actual earnings less than mean consensus forecast, the absolute value of actual earnings less than median consensus forecast, deflation by both the mean and median forecasts instead of by stock price, etc. See the robustness section for further details.

[14] This is especially the case for *ACCURACY* as it is deflated by stock price. Extremely low priced stocks could have a large impact on this variable as they could produce large outliers due to a denominator effect. In robustness testing, we also re-estimate the results after dropping low priced stocks (stocks < \$5 per share).

[15] As expected, our alternative measures correlate highly with the original measure. For instance, total fair value assets scaled by total assets and *FV_INTENSITY* have a highly significant Pearson correlation coefficient of 0.936. The alternative for Level 1 measurements and *LVL_ONE_INTENSITY* has a 0.960 correlation, The alternative for Level 2 measurements and *LVL_TWO_INTENSITY* has a 0.924 correlation, and the alternative for level three measurements and *LVL_THREE_INTENSITY* has a 0.782 correlation. As a result, each measurement and alternative measurement appear to be capturing the same construct.

number of unique analysts who issue a forecast for firm *i* for the period ending at *t*.

Industry and year fixed effects are also employed to control for phenomena at the industry and time levels that may affect overall forecasting.[16] For example, certain industries or types of firms may simply be more difficult to forecast (Barron et al., 2002), and certain time periods, especially those of severe economic distress, may result in vastly different forecasting outcomes. To the extent that these correlate with our variables of interest, it is necessary to control for both industry and time. We control for industry using indicator variables for firm *i*'s two-digit SIC code. We control for time using indicator variables for each fiscal year.

b. Sample selection

The sample is primarily formulated using three databases. All financial statement and segment information is obtained from Compustat. All information pertaining to analysts and analyst forecasts are obtained from the I/B/E/S unadjusted detail file.[17] Consensus forecasts are computed using the median of the final forecasts for all analysts following firm *i*, after stopped and excluded estimates are accounted for. Any firms lacking analyst coverage are thus dropped from the analysis. All information pertaining to stock prices is obtained from the CRSP database. All forecasting and financial statement information employed is annual in nature. Only those firm-years fully populated with all variables are included in the final sample.

Our sample begins with firm-years beginning on November 15, 2007, and ends with firm-years ending as of December 31, 2013.[18] After merging the CRSP-Compustat and I/B/E/S databases, dropping all firm-years without complete information on the variables, and performing truncation of the dependent variable, we are left with a sample size of 13,990 firm-year observations for *ACCURACY*.

IV. Main empirical analysis

a. Descriptive statistics

Table 1 details the descriptive statistics for all of the variables employed in the main analyses of this study. Unless otherwise noted, the sample statistics are for the full sample of 13,990 firm-year observations. The *ACCURACY* measurements are negative by construction (multiplied by negative one) to ensure easier interpretation of regression coefficients and correlations: variables that are thus positively correlated with accuracy will receive a positive coefficient on our measurement, *ACCURACY*.

ACCURACY has a mean value of −0.038 and a median value of −0.006. This means that the consensus forecast error is thus approximately 3.8% of share price for the mean value and 0.6% of share price for the median. Even with the winsorization of *ACCURACY*, the differences between the mean and median are noticeable for the dependent variables. Similar differences between the mean and median values are noted in prior literature (Duru & Reeb, 2002; Lehavy et al., 2011; Lang & Lundholm, 1996).

The median firm-year within the sample has approximately \$1.4 billion in total assets (7.229 exponentiated × \$1,000,000). Losses occur in approximately 26.1% of the sample, which is not surprising given that a substantial portion of the sample falls within the years of the 2007–2009 financial crisis. Overall, the firm-years do not exhibit high degrees of financial leverage, as total interest bearing debt is only 21.8% of total firm assets. As expected, the vast majority of firms have market-to-book values that are greater than one. The average firm year appears to have analyst following of 6.7 analysts. A substantial portion of the sample is comprised of firm-years with two or more analysts following the firm. Fair value measurements are approximately 15.7% of total assets on average, and the bulk of these fall into the Levels 1 and 2 SFAS No. 157 specifications.[19] A small minority of fair value measurements (0.9% of total assets) fall within the SFAS No. 157 Level 3 categorization.

Panels B and C breakdown the variables between financial industry firms and non-financial industry firms. Overall, the levels of fair value measurement are higher for financial industry firms, as expected. The average *FV_INTENSITY* for financial firms is 26.1% of total assets, versus 13.6% for non-financial industry firms. Financial industry firms also have much higher levels of the more exotic fair value measurements, as the magnitude of Level 2 and 3 measurements are substantially higher in both cases. This signals that substantial differences exist between the two sub-samples of firms, and it also suggests that differing business motives and operational needs likely explain the quantitative and qualitative differences between the two.

Table 2 details univariate correlations (both Pearson and Spearman) for the entire sample. All correlations statistically significant at the 0.10 level or lower are bold and italicized.

ACCURACY is positively related to firm size and negatively related to the firm being in a loss position. Furthermore, earnings volatility and leverage appear to be negatively correlated with *ACCURACY*. Analyst following, as expected, appears to be correlated with more favorable forecasting outcomes: it is positively related to accuracy and negatively related to dispersion. As expected, the fair value measurement variables all express positive correlations.

b. Hypotheses tests: fair value measurements

Tables 3 through 4 provide results of our hypotheses tests on the relevance of fair value measurements to analysts. Table 3 concerns itself with testing Hypothesis 1, and Table 4 serves as the main test for Hypothesis 2. Table 3 employs Eq. (1); Table 4 employs Eq. (2).

Table 3 employs Eq. (1) to measure the effect of the variable of interest, *FV_INTENSITY*, upon *ACCURACY*. Column 1 utilizes the entire sample, while Columns 2 and 3 break the sample down between financial industry and non-financial industry firms. All analyses employ ordinary least squares.[20] The sample in Column 1 is the overall sample size of 13,990 firm-years. All *t*-statistics are computed using firm-level cluster robust standard errors.

The results reflect an association between fair value measurements and *ACCURACY*, and they support Hypothesis 1. In Column 1, the coefficient is positive (0.022) and highly significant from a statistical standpoint (t-statistic = 5.943).[21] This suggests that higher levels of fair

[16] In the untabulated analysis, we include additional macroeconomics variables as control variables, such as market liquidity (we use the weighted-average bid-ask spread) and the unemployment rate. Our results remain unchanged.

[17] In robustness testing, we also employ the I/B/E/S summary file to capture the mean and median consensus forecasts for each firm and re-estimate our main tables to ensure that our choice to employ the detail file is not driving our results.

[18] Firm–years beginning before November 15, 2007, are not included because these firm years predate the inception of SFAS No. 157 disclosures. SFAS No. 157 disclosures enable accurate measurement of our variables of interest.

[19] The sum of Level 1, 2, and 3 measurements only approximate and do not equal total fair value measurements within Table 1 due to the individual winsorization of each variable.

[20] The results are similar and statistically strengthened if GLS (Generalized Linear Model) is employed.

[21] To better ensure that time invariant traits at the firm level are not somehow driving our results, we also estimate the model in Column 1 using firm level fixed effects (untabulated). Our overall inferences remain unchanged and the actual magnitude of the result is enlarged. *FV_INTENSITY* remains positively related to *ACCURACY* (coefficient = 0.039) and continues to exhibit statistical strength (t-statistic = 3.97) despite a large loss in degrees of freedom. We also specify Column 1 as a changes model, effectively losing one year of sample size to compute the changes in each variable for each year. This specification also yields similar results. The coefficient for *FV_INTENSITY* is positive (coefficient = 0.033) and statistically significant (t-statistic = 3.162). Firm-specific traits do not appear to be a source of endogeneity for the results documented in Table 3.

Table 1
Descriptive statistics.
Panel A presents the descriptive statistics for the full sample of 13,990 firm-year observations. All variables are defined in the Appendix A.
Panel B presents the descriptive statistics for the subsample of 11,652 non-financial industry firm-year observations. All variables are defined in the Appendix A.
Panel C presents the descriptive statistics for the subsample of 2338 financial industry firm-year observations. All variables are defined in the Appendix A.

	N	Mean	Std. dev.	10th %tile	25th %tile	Median	75th %tile	90th %tile
Panel A								
ACCURACY	13,990	−0.038	0.108	−0.072	−0.020	−0.006	−0.002	−0.001
BIAS	13,990	0.020	0.090	−0.016	−0.004	0.000	0.009	0.050
FV_INTENSITY	13,990	0.157	0.225	0.000	0.002	0.044	0.224	0.508
LVL_ONE_INTENSITY	13,990	0.064	0.133	0.000	0.000	0.001	0.061	0.216
LVL_TWO_INTENSITY	13,990	0.079	0.152	0.000	0.000	0.004	0.084	0.280
LVL_THREE_INTENSITY	13,990	0.009	0.035	0.000	0.000	0.000	0.002	0.020
SIZE	13,990	7.241	1.819	4.897	5.937	7.229	8.437	9.663
LOSS	13,990	0.261	0.439	0.000	0.000	0.000	1.000	1.000
EARN_VOLATILITY	13,990	0.054	0.078	0.005	0.012	0.027	0.060	0.128
LEVERAGE	13,990	0.218	0.207	0.000	0.037	0.017	0.341	0.509
MKTBK	13,990	1.775	1.194	0.954	1.050	1.361	1.993	3.123
SEGMENTS	13,990	2.289	1.812	1.000	1.000	1.000	3.000	5.000
EARN_MOMENTUM	13,990	0.086	0.269	0.003	0.007	0.018	0.050	0.150
FOLLOWING	13,990	6.748	5.701	1.000	2.000	5.000	9.000	15.000
Panel B - non-financial industry firms								
ACCURACY	11,652	−0.034	0.099	−0.065	−0.019	−0.006	−0.002	−0.001
BIAS	11,652	0.017	0.082	−0.016	−0.004	0.000	0.008	0.044
FV_INTENSITY	11,652	0.136	0.213	0.000	0.001	0.025	0.185	0.466
LVL_ONE_INTENSITY	11,652	0.070	0.140	0.000	0.000	0.002	0.072	0.239
LVL_TWO_INTENSITY	11,652	0.055	0.130	0.000	0.000	0.002	0.027	0.198
LVL_THREE_INTENSITY	11,652	0.008	0.030	0.000	0.000	0.000	0.001	0.018
SIZE	11,652	7.040	1.802	4.744	5.725	6.952	8.269	9.475
LOSS	11,652	0.278	0.448	0.000	0.000	0.000	1.000	1.000
EARN_VOLATILITY	11,652	0.061	0.081	0.008	0.016	0.032	0.068	0.142
LEVERAGE	11,652	0.226	0.211	0.000	0.021	0.194	0.355	0.514
MKTBK	11,652	1.884	1.234	0.956	1.135	1.477	2.144	3.307
SEGMENTS	11,652	2.437	1.862	1.000	1.000	1.000	4.000	5.000
EARN_MOMENTUM	11,652	0.077	0.241	0.003	0.007	0.017	0.048	0.141
FOLLOWING	11,652	7.041	5.814	1.000	3.000	5.000	10.000	15.000
Panel C - financial industry firms								
ACCURACY	2338	−0.056	0.144	−0.129	−0.026	−0.007	−0.002	−0.001
BIAS	2338	0.036	0.120	−0.016	−0.005	0.000	0.012	0.094
FV_INTENSITY	2338	0.261	0.252	0.003	0.088	0.181	0.346	0.680
LVL_ONE_INTENSITY	2338	0.035	0.091	0.000	0.000	0.001	0.020	0.116
LVL_TWO_INTENSITY	2338	0.196	0.192	0.000	0.038	0.153	0.268	0.503
LVL_THREE_INTENSITY	2338	0.016	0.050	0.000	0.000	0.000	0.007	0.031
SIZE	2338	8.242	1.553	6.614	7.260	8.037	9.157	10.291
LOSS	2338	0.178	0.383	0.000	0.000	0.000	0.000	1.000
EARN_VOLATILITY	2338	0.019	0.045	0.002	0.003	0.007	0.017	0.039
LEVERAGE	2338	0.178	0.184	0.023	0.056	0.112	0.220	0.465
MKTBK	2338	1.231	0.767	0.953	0.982	1.021	1.105	1.570
SEGMENTS	2338	1.550	1.313	1.000	1.000	1.000	1.000	4.000
EARN_MOMENTUM	2338	0.134	0.377	0.003	0.008	0.020	0.063	0.250
FOLLOWING	2338	5.289	4.842	1.000	2.000	4.000	7.000	12.000

value measurements result in higher levels of forecast accuracy, which supports the rejection of the null form of Hypothesis 1.[22]

In regard to practical significance, our results appear to be practically significant. A one-standard deviation change (0.225) in *FV_INTENSITY* results in a 0.005 (0.225×0.022) change in accuracy. Given that the mean absolute value of *ACCURACY* is 0.038, this results in an approximate change of 13.2% (0.005 / 0.038) around the mean. This change is much more pronounced when using the median absolute value of *ACCURACY* (0.006), which results in an approximate change of 83.3% (0.005 / 0.006) around the median value. Higher levels of fair value measurement are thus associated with significantly higher levels of accuracy.

Many of the other variables within the regressions appear to be exhibiting the relation to *ACCURACY* that one would expect. *SIZE* is positively related to *ACCURACY*, and *LOSS* is negatively related. Earnings volatility reduces accuracy. Financial leverage is associated with lower levels of forecasting accuracy, while greater analyst following results in higher levels of forecasting accuracy. This likely reflects greater dissemination of information as more analysts follow a firm.

Since the sample is comprised of financial industry and non-financial industry firms, Columns 2 and 3 explore whether fair value intensity affects these two sub-samples in a differential manner. The results in Column 2 fail to find any kind of relation between forecast accuracy and *FV_INTENSITY* as the coefficient is negative but not statistically significant. However, the results in Column 3 show that a strong positive relation exists between *FV_INTENSITY* and forecast accuracy for non-financial industry firms. The coefficient is positive (0.023) and highly significant (*t*-statistic = 5.625). These results suggest that fair value measurements appear to have different impacts upon the type of firm holding them.

We posit that these results may be a product of both the on-average operational and the holding purposes for these types of assets within each firm type. These potential differences likely also result in differences in accounting treatment, which ultimately affects reported earnings and the ability of analysts to forecast such earnings. For instance, we posit that financial industry firms are more likely to hold fair value assets for short-term trading purposes than are non-financial industry

[22] These results hold if *FV_INTENSITY* is replaced with an alternative measure excluding fair value liability measurements and employing only fair value asset measurements.

Table 2
Correlation matrices.
Table 2 presents Pearson (lower left-hand side) and Spearman (upper right-hand side) correlation coefficient matrices for all firms in the sample. All variables are defined in the Appendix A. Bold and italicized values indicate significance at the 0.10 level or stronger (based on two-tailed tests).

	ACCURACY	*BIAS*	*FV_INTENSITY*	*LVL_ONE_INTENSITY*	*LVL_TWO_INTENSITY*	*LVL_THREE_INTENSITY*	*SIZE*	*LOSS*	*EARN_VOLATILITY*	*LEVERAGE*	*MKTBK*	*SEGMENTS*	*EARN_MOMENTUM*	*FOLLOWING*
ACCURACY		***−0.177***	***−0.031***	***0.022***	***0.015***	***−0.037***	***0.203***	***−0.412***	***−0.290***	***−0.034***	***0.352***	***0.068***	***−0.511***	***0.315***
BIAS	***−0.847***		***−0.082***	***−0.094***	***−0.043***	***−0.023***	***−0.031***	***0.235***	***0.030***	***0.067***	***−0.178***	***−0.028***	−0.001	***−0.083***
FV_INTENSITY	0.006	***−0.048***		***0.735***	***0.668***	***0.408***	***0.020***	***0.066***	***0.052***	***−0.219***	***0.062***	***−0.149***	***0.061***	***0.060***
LVL_ONE_INTENSITY	−0.048	***0.014***	***0.674***		***0.253***	***0.229***	***−0.024***	***0.041***	***0.126***	***−0.218***	***0.172***	***−0.019***	0.001	***0.100***
LVL_TWO_INTENSITY	***0.016***	***−0.032***	***0.729***	***0.064***		***0.243***	***0.275***	***−0.035***	***−0.173***	***−0.035***	***−0.103***	***−0.092***	0.012	***0.097***
LVL_THREE_INTENSITY	***0.005***	***−0.046***	***0.350***	***0.135***	***0.063***		***0.163***	0.013	***−0.069***	***−0.050***	***−0.091***	***−0.021***	***0.036***	***0.047***
SIZE	***0.126***	***−0.075***	***−0.089***	***−0.230***	***0.095***	***−0.068***		***−0.288***	***−0.512***	***0.375***	***−0.228***	***0.183***	***−0.180***	***0.421***
LOSS	***−0.383***	***0.349***	***0.120***	***0.137***	***0.029***	***0.085***	***−0.301***		***0.378***	***0.034***	***−0.127***	***−0.121***	***0.372***	***−0.188***
EARN_VOLATILITY	***−0.183***	***0.087***	***0.250***	***0.292***	***0.053***	***0.143***	***−0.458***	***0.358***		***−0.128***	***0.258***	***−0.107***	***0.356***	***−0.104***
LEVERAGE	***−0.077***	***0.075***	***−0.162***	***−0.150***	***−0.122***	0.010	***0.253***	***0.082***	***−0.035***		***−0.155***	***0.134***	0.005	***0.028***
MKTBK	***0.133***	***−0.127***	***0.217***	***0.292***	***0.046***	***0.039***	***−0.272***	***0.016***	***0.355***	***−0.107***		***−0.034***	***−0.233***	***0.260***
SEGMENTS	***0.084***	***−0.063***	***−0.155***	***−0.102***	***−0.118***	***−0.041***	***0.219***	***−0.118***	***−0.162***	***0.083***	***−0.113***		***−0.094***	***0.031***
EARN_MOMENTUM	***−0.602***	***0.401***	***0.032***	***0.028***	0.005	***0.069***	***−0.112***	***0.263***	***0.201***	***0.047***	***−0.058***	***−0.073***		***−0.244***
FOLLOWING	***0.187***	***−0.138***	***0.024***	0.004	***0.045***	***−0.042***	***0.453***	***−0.179***	***−0.119***	−0.005	***0.192***	***0.049***	***−0.160***	

Table 3
Accuracy analysis.
Table 3 presents the results of the ordinary least squares analysis for Eq. (1). The dependent variable is *ACCURACY*. All variables are defined in the Appendix A. Column 1 presents the results for the entire sample of firms, while Columns 2 and 3 break the sample into financial industry and non-financial industry sub-samples. Robust two-tailed *t*-statistics are presented in parentheses below the coefficients. *, ** and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively. All standard errors are clustered at the firm level. Bold values indicate the variable of interest.

	(1)	(2)	(3)
		Financials	Non-financials
	ACCURACY	*ACCURACY*	*ACCURACY*
FV_INTENSITY	**0.022*****	**−0.004**	**0.023*****
	(**5.943**)	(**−0.530**)	(**5.625**)
SIZE	0.001**	0.001	0.002***
	(1.976)	(0.671)	(3.277)
LOSS	−0.055***	−0.135***	−0.042***
	(−20.659)	(−12.476)	(−16.925)
EARN_VOLATILITY	−0.063***	−0.118	−0.081***
	(−3.429)	(−1.361)	(−4.204)
LEVERAGE	−0.021***	−0.039**	−0.024***
	(−4.241)	(−2.241)	(−4.680)
MKTBK	0.006***	0.003	0.007***
	(8.863)	(0.853)	(9.952)
SEGMENTS	0.001**	0.000	0.001***
	(2.165)	(0.067)	(2.867)
EARN_MOMENTUM	−0.208***	−0.195***	−0.201***
	(−28.910)	(−15.439)	(−21.953)
FOLLOWING	0.000***	0.001	0.000*
	(2.603)	(1.484)	(1.843)
INDUSTRY F.E.'s	Yes	Yes	Yes
YEAR F.E.'s	Yes	Yes	Yes
INTERCEPT	Yes	Yes	Yes
N	13,990	2338	11,652
R-squared	0.467	0.608	0.425

Table 4
Fair value levels analysis.
Table 4 presents the results of the ordinary least squares analysis for Eq. (2). All variables are defined in the Appendix A. Column 1 presents the results for the entire sample of firms, while Columns 2 and 3 break the sample into financial industry and non-financial industry sub-samples. Robust two-tailed *t*-statistics are presented in parentheses below the coefficients. *, ** and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All standard errors are clustered at the firm level. Bold values indicate the variables of interest.

	(1)	(2)	(3)
		Financials	Non-financials
	ACCURACY	*ACCURACY*	*ACCURACY*
LVL_ONE_INTENSITY	**0.022*****	**−0.052*****	**0.023*****
	(**3.898**)	(**−2.775**)	(**3.968**)
LVL_TWO_INTENSITY	**0.024*****	**0.011**	**0.022*****
	(**4.863**)	(**0.930**)	(**4.665**)
LVL_THREE_INTENSITY	**0.025**	**−0.008**	**0.036**
	(**0.994**)	(**−0.186**)	(**1.131**)
SIZE	0.001*	0.001	0.002***
	(1.952)	(0.486)	(3.292)
LOSS	−0.055***	−0.134***	−0.042***
	(−20.671)	(−12.467)	(−16.941)
EARN_VOLATILITY	−0.062***	−0.116	−0.080***
	(−3.383)	(−1.388)	(−4.165)
LEVERAGE	−0.021***	−0.042**	−0.024***
	(−4.224)	(−2.421)	(−4.671)
MKTBK	0.006***	0.003	0.007***
	(8.708)	(1.067)	(9.930)
SEGMENTS	0.001**	−0.000	0.001***
	(2.166)	(−0.037)	(2.850)
EARN_MOMENTUM	−0.208***	−0.195***	−0.201***
	(−28.810)	(−15.487)	(−21.866)
FOLLOWING	0.000***	0.001*	0.000*
	(2.620)	(1.651)	(1.862)
INDUSTRY F.E.'s	Yes	Yes	Yes
YEAR F.E.'s	Yes	Yes	Yes
INTERCEPT	Yes	Yes	Yes
N	13,990	2338	11,652
R-squared	0.466	0.609	0.425

firms. This would result in fair value gains and losses being reported in operating earnings, potentially increasing the volatility of such earnings and making them ultimately more difficult to forecast.

On the other hand, we posit that non-financial industry firms are more likely to have such assets classified for available for sale, which entails no earnings impact for the changes in the asset values from one period to the next. This is based on the fact that such companies, on average, exist to operate, not to trade or speculate in financial markets. To the extent that this is true, this means that the larger a firm's asset base is invested in fair value assets, the more benign its overall asset base is to forecasted earnings. Another potential benefit to having a larger proportion of fair value assets as being classified as available for sale is that it could potentially allow the managers of the firm to selectively recognize gains in order to "manage" earnings within the threshold of analyst forecasts if such items are not explicitly excluded from analyst forecasts.

Anecdotally, we explore these ideas with the most recent 10-K filings of a large and well-known financial industry firm: Bank of America, and a large and well-known non-financial industry firm – Apple. Apple was specifically chosen because of its well-documented propensity to hold vast quantities of investment securities purchased by its high levels of free cash flow. According to the Bank of America's December 31, 2015, form 10-K, it had approximately $633 billion in fair value asset measurements. Of these measurements, 28% ($177 billion) were classified as trading account assets, and derivative assets make up the bulk of the other fair value assets. These trading assets included U.S. government securities ($49 billion), corporate securities ($26 billion), equities ($63 billion), sovereign debt ($29 billion), and mortgage trading loans/asset backed securities ($10 billion). Only a small minority of these trading securities ($6 billion) take the form of level three measurements. A similar pattern holds for the December 31, 2014, form 10-K.

Apple's September 26, 2015, form 10-K paints a different picture. Apple possessed $206 billion in fair value assets. None of these fall under the classification for Level 3 measurements, and none are classified as trading securities within Apple's disclosure of financial instruments – Apple classifies all marketable debt and equity securities as available for sale. The largest single asset class is corporate securities of $117 billion and Apple discloses both aggregate unrecognized gains and losses for these. Thus, Apple does not appear to be subjected to the earnings volatility inherent to trading asset classification.[23]

Thus far, we have shown that fair value measurements appear to affect analyst forecasting outcomes by improving them, but most of this improvement appears to be related to non-financial industry firms and it may be a result of how these assets are accounted for. SFAS No. 157 supplied financial statement users with further information to assess the qualitative aspect of fair value measurements. In Table 4, we explore this aspect, employ Eq. (2), and directly test Hypothesis 2.

Table 4 is structured similar to Table 3. Column 1 displays the results for the entire sample, while Columns 2 and 3 break the results into subsamples of financial industry and non-financial industry firms. Column 1 yields interesting results in regard to *ACCURACY*. Both Levels 1 and 2 measurements reflect similar relations (Column 1 coefficients = 0.022 and 0.024) to *ACCURACY* and generally support the findings within Table 3.[24] Both are statistically significant. No discernable result appears for *LVL_THREE_INTENSITY*. These results provide support for the rejection of the null form of Hypothesis 2.

Similar to Table 3, Table 4 also exhibits high levels of practical significance. Using Column 1, a one standard deviation change in the variables of interest, *LVL_ONE_INTENSITY*, and *LVL_TWO_INTENSITY* (0.133 and 0.152, respectively), results in respective changes of 0.0029 (0.133×0.022) and 0.0036 (0.152×0.024) to *ACCURACY*. Given that the mean absolute value of *ACCURACY* is 0.038, this results in approximate changes of 7.7% (0.0029 / 0.038) and 9.6% (0.0036 / 0.038) around the mean, respectively. This change is much more pronounced when using the median absolute value of *ACCURACY* (0.006), which results in approximate changes of 50% (0.0029 / 0.006), 62% (0.0018 / 0.006) and −13.3% (−0.0008 / 0.006) around the median, respectively.

Columns 2 and 3 further explore the effect for financial industry versus non-financial industry firms. The pattern holds for non-financial industry firms as the coefficients for *LVL_ONE_INTENSITY* and *LVL_TWO_INTENSITY* are both positive and highly significant. However, an interesting result emerges for financial industry firms. While *LVL_TWO_INTENSITY* and *LVL_THREE_INTENSITY* appear to have no discernable result, *LVL_ONE_INTENSITY* appears to have a negative and statistically significant impact on forecast accuracy. We posit that this result is a function of the previously mentioned purpose for the assets. If financial institutions, by and large, hold Level 1 measurements for trading purposes, this could induce more volatility into the actual earnings of the firm and make forecasting these earnings more difficult. Our anecdotal findings in Footnote 21 appear to support this notion.

Overall, these results for Tables 3 and 4 stand in stark contrast to those of Magnan et al. (2015). While Magnan et al. (2015) find an overall positive relationship between fair value measurements as forecasting outcomes, their relatively small sample is comprised of only banks. Our results for financial industry firms in Table 4 contrast these results as we find a negative relationship for Level 1 measurements.

Regarding non-financial industry firms, accuracy appears to be highest when assets are easily measured and verified (i.e., Levels 1 and 2 measurements). This suggests and is supportive of the notion that higher levels of transparency result in more favorable forecasting outcomes. Furthermore, the fact that these assets are more likely to be accounted for as available for sale securities diminishes their overall impact to earnings on a quarter by quarter basis, except for when they are sold. The timing of such sales can take place at the discretion of management.

Given these somewhat contradictory results to those of Magnan et al. (2015), we next examine the relationship between fair value measurements and analysts' information environments in times of economic stability versus economic distress. The sample of Magnan et al. (2015) effectively takes place just before and during the financial crisis of 2007–2009. Even though we posit that we expect their fair value measurement could impact forecast accuracy in a very different manner due to their qualitative nature, we have not thus far found any consistent explanation for why our results differ from those of Magnan et al. (2015). One potential confound driving this might be the financial crisis itself, as it affected these firms disproportionately, making forecasting a difficult task. To further explore this notion, we produce Table 5, which is a reproduction of Tables 3 and 4 with regressions for the period of the financial crisis and the period just after the financial crisis.[25]

The results of Table 5 appear to explain why our results differ from those of Magnan et al. (2015). During the crisis years, fair value measurements for financial industry firms are positively related to *ACCURACY* (coefficient = 0.052, *t*-statistic = 1.855). This result appears to echo those of Magnan et al. (2015) and tie our overall findings into theirs. However, during the post-crisis period, this relation flips and becomes negative (coefficient = −0.017, *t*-statistic = −2.365). This subsequent negative relation for financial industry firms appears to support our discussion in the previous section that the qualitative nature of the assets has a different effect for financial industry firms – note the relation is

[23] We further extend this by examining the most recent 10-Ks for four additional large non-financial industry firms (Exxon, Google, Amazon, and Microsoft) and four additional large financial industry firms (JP Morgan Chase, Wells Fargo, Citigroup, and Visa). The criteria of choosing these firms was market capitalization. In all cases, the pattern is similar for the non-financial industry firms: no disclosed trading assets and all investments are labeled and accounted for using available for sale rules. Furthermore, in all cases, the pattern holds for the financial industry firms as all possess substantial and material levels of trading assets in asset classes similar to those of Bank of America.

[24] A changes specification of Column 1 also yields similar results in terms of direction and statistical significance.

[25] Our cut-off for the financial crisis is December 31, 2009.

Table 5
Financial crisis analysis.
Table 5 presents the results of the ordinary least squares analysis for the results of Tables 3 and 4, with the samples being bifurcated at 12/31/2009 for the financial crisis. All variables are defined in the Appendix A. Robust two-tailed *t*-statistics are presented in parentheses below the coefficients. *, ** and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All standard errors are clustered at the firm level. Bold values indicate the variables of interest.

Financial Firms			Non - Financial Firms		
	Crisis *ACCURACY*	Non-Crisis *ACCURACY*		Crisis *ACCURACY*	Non-Crisis *ACCURACY*
FV_INTENSITY	**0.052***	**-0.017****	***FV_INTENSITY***	**0.032*****	**0.019*****
	(1.855)	**(-2.365)**		**(3.351)**	**(4.250)**
CONTROLS	Yes	Yes	CONTROLS	Yes	Yes
INDUSTRY F.E.'s	Yes	Yes	INDUSTRY F.E.'s	Yes	Yes
YEAR F.E.'s	No	No	YEAR F.E.'s	No	No
INTERCEPT	Yes	Yes	INTERCEPT	Yes	Yes
N	617	1,721	N	3,496	8,156
Financial Firms			Non - Financial Firms		
	Crisis *ACCURACY*	Non-Crisis *ACCURACY*		Crisis *ACCURACY*	Non-Crisis *ACCURACY*
LVL_ONE_INTENSITY	**-0.062**	**-0.040****	***LVL_ONE_INTENSITY***	**0.024***	**0.022*****
	(-1.193)	**(-2.141)**		**(1.940)**	**(3.171)**
LVL_TWO_INTENSITY	**0.063**	**-0.015**	***LVL_TWO_INTENSITY***	**0.037*****	**0.015*****
	(1.438)	**(-1.337)**		**(2.958)**	**(3.504)**
LVL_THREE_INTENSITY	**0.100**	**-0.003**	***LVL_THREE_INTENSITY***	**0.075**	**-0.002**
	(0.576)	**(-0.071)**		**(1.555)**	**(-0.060)**
CONTROLS	Yes	Yes	CONTROLS	Yes	Yes
INDUSTRY F.E.'s	Yes	Yes	INDUSTRY F.E.'s	Yes	Yes
YEAR F.E.'s	No	No	YEAR F.E.'s	No	No
INTERCEPT	Yes	Yes	INTERCEPT	Yes	Yes
N	617	1,721	N	3,496	8,156

opposite and significant for non-financial industry firms in the post-crisis era (coefficient = 0.019, *t*-statistic = 4.250), and the overall results for non-financial industry firms mirror those in both Tables 3 and 4.

The most curious element is what might have caused the relation for financial industry firms to be positive during the crisis era – fair value assets aided in forecast accuracy for financial firms during this period. One potential explanation lies in the fact that the FASB issued several staff positions in early 2009 that essentially relaxed the impairment rules for fair value assets when markets become illiquid. Since the fair value accounting rules were relaxed, it may have been possible for management to obtain desired earnings levels, thus enhancing the accuracy of analysts' forecasts, through these relaxed rules.

A second reason for this overall result may lay in the overwhelming downward direction of asset price movements during this time. Almost all asset classes were under severe duress, except of U.S. government bonds, foretelling large losses for firms that held such fair value measurements as trading assets on their balance sheets. This potentially provided analysts with a unique situation to better build these price movements into their forecasts and expectations for earnings. Since SFAS No. 157 disclosures are typically fairly opaque and tend to "lump" asset classes such as equities together, in normal times developing an overall expectation for the impact of price movements upon earnings can potentially prove more difficult as most assets within classes are experiencing more randomness in their price movements. Overall, the results of this analysis appear to support an explanation for why we fail to find an overall result for financial industry firms for the entire breadth of our sample.

This result also appears to mimic that of Magnan et al. (2015) because they initially document no relationship between fair value measurements and forecast accuracy, but as their sample years get closer to the financial crisis, a positive relationship intensifies. They primarily attribute this change to an enhanced information environment brought about by the inception of SFAS No. 157 in 2007. However, the inception of SFAS No. 157 also closely aligns with the onset of the financial crisis and the relaxation of impairment rules for fair value measurements. If the information environment were indeed enhanced by the onset of SFAS No. 157, we would not expect the results to change as they do in Table 6 for the period after the financial crisis. Thus, the effect of SFAS No. 157 on the overall information environment remains questionable.

c. Additional analysis - bias

Given our results regarding *ACCURACY*, it would be of interest to explore the relation between our primary variable of interest, *FV_INTENSITY*, and bias in analyst forecasts. Analyst forecasts have historically been shown to exhibit a chronic form of positive bias (i.e., being overly optimistic), but various items have been found in the prior literature to limit this chronic positive bias (Hong & Kacperczyk, 2010; McNichols & O'Brien, 1997). Our next analysis thus seeks to determine the effects of fair value assets upon forecast bias.

Forecast bias is measured with the variable *BIAS*, which is equal to the difference between the consensus forecast and actual earnings, deflated by stock price. The only material difference between the calculations of *BIAS* and *ACCURACY* is that *ACCURACY* employs the absolute value of this difference, while *BIAS* does not. Eqs. (1) and (2) are re-estimated using *BIAS* as the dependent variable. As a result, Table 6 has primarily the same forms as Tables 3 and 4. All robust standard errors are clustered at the firm level.

Within Column 1, fair value measurements exhibit fairly strong negative relationships to *BIAS* (coefficient = −0.029), and this relationship is highly statistically significant at the 0.01 level (*t*-statistic = −7.432). In Columns 2 and 3, a similar pattern also emerges in that the bulk of the result appears to be attributable to non-financial industry firms. Columns 4 through 6 echo the analysis in Table 4. In Column 4, the results appear to indicate that all fair value measurement levels reduce chronic analyst bias as all coefficients are negative and statistically significant. Much of this appears to be driven, again, by non-financial firms as the same pattern appears in Column 6. Interestingly, Level 1 measurement appears to have a significant positive relationship to analyst bias in Column 5. These results appear to support previous findings and suggest

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Table 6
Bias analysis.
Table 6 presents the results of the ordinary least squares analysis for Eqs. (1) and (2) with *BIAS* serving as the dependent variable. All variables are defined in the Appendix A. Robust two-tailed *t*-statistics are presented in parentheses below the coefficients. *, ** and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All standard errors are clustered at the firm level. Bold values indicate the variables of interest.

	(1) BIAS	(2) Financials BIAS	(3) Non-financials BIAS	(4) BIAS	(5) Financials BIAS	(6) Non-financials BIAS
FV_INTENSITY	**−0.029***** **(−7.432)**	**0.004** **(0.618)**	**−0.031***** **(−7.174)**			
LVL_ONE_INTENSITY				**−0.033***** **(−5.203)**	**0.039**** **(2.213)**	**−0.034***** **(−5.232)**
LVL_TWO_INTENSITY				**−0.027***** **(−5.692)**	**−0.004** **(−0.384)**	**−0.027***** **(−5.751)**
LVL_THREE_INTENSITY				**−0.047**** **(−2.039)**	**−0.035** **(−0.808)**	**−0.048*** **(−1.667)**
SIZE	−0.000 (−0.499)	−0.001 (−1.011)	−0.001* (−1.824)	−0.000 (−0.540)	−0.001 (−0.882)	−0.001* (−1.871)
LOSS	0.057*** (22.725)	0.138*** (14.750)	0.043*** (18.394)	0.057*** (22.736)	0.138*** (14.734)	0.043*** (18.392)
EARN_VOLATILITY	−0.017 (−0.929)	0.047 (0.601)	0.004 (0.213)	−0.017 (−0.925)	0.061 (0.818)	0.004 (0.184)
LEVERAGE	0.017*** (3.516)	0.017 (1.096)	0.023*** (4.308)	0.017*** (3.480)	0.021 (1.373)	0.023*** (4.298)
MKTBK	−0.003*** (−3.633)	−0.000 (−0.187)	−0.003*** (−4.726)	−0.002*** (−3.487)	−0.002 (−0.674)	−0.003*** (−4.714)
SEGMENTS	−0.000 (−1.324)	−0.001 (−0.504)	−0.001* (−1.891)	−0.000 (−1.318)	−0.001 (−0.487)	−0.001* (−1.853)
EARN_MOMENTUM	0.109*** (13.459)	0.100*** (8.443)	0.099*** (9.076)	0.109*** (13.472)	0.100*** (8.478)	0.099*** (9.087)
FOLLOWING	−0.000 (−1.501)	−0.000 (−0.572)	−0.000 (−0.997)	−0.000 (−1.526)	−0.000 (−0.580)	−0.000 (−1.045)
INDUSTRY F.E.'s	Yes	Yes	Yes	Yes	Yes	Yes
YEAR F.E.'s	Yes	Yes	Yes	Yes	Yes	Yes
INTERCEPT	Yes	Yes	Yes	Yes	Yes	Yes
N	13,990	2338	11,652	13,990	2338	11,652
R-squared	0.288	0.482	0.237	0.288	0.483	0.237

that qualitative differences likely exist for the purpose of fair value holdings between these two major industry classifications.

d. Additional robustness testing

Our first set of robustness tests involves the dependent variables. More specifically, we change *ACCURACY* so that it is based upon the mean consensus forecast instead of the median and find similar results. Furthermore, instead of winsorizing the dependent variables at the 2% and 98% levels to limit statistical outliers, we instead truncate the sample and our results are predominantly unchanged. We also employ I/B/E/S summary data instead of the detail data to calculate these variables and find similar inferences.

Our descriptive statistics in Table 1 suggest that a substantial proportion of our firms do not have any fair value measurements. We examine whether this fact is driving our results. After dropping all firm-year observations with zero fair value assets, we attain similar results for our main tests. Thus, the large amount of zero fair value asset firm-years do not appear to be biasing our results in any way.

We also further control for analyst traits beyond analyst following alone. Analyst traits have been well documented to affect forecasting outcomes (Jacob et al., 1999; Clement, 1999). In doing so, we re-estimate Tables 3 and 4 with the following additional control variables at the firm level: the average analyst portfolio size, the average level of analyst specialization, the average level of analyst experience, the average tenure of the analysts, the average forecasting frequency of the analysts, and the average rank of the brokerage firms following the firm. Our results are robust to the inclusion of these additional measures. Specific analyst traits do not appear to be correlated with omitted variables that are biasing our findings.

V. Conclusion

This study asks an interesting and novel question regarding the impact of fair value measurements on the forecasts of financial analysts and builds upon the work of Magnan et al. (2015). The study of what impacts forecasting outcomes is an important area of research as forecasts of earnings and other signals of future cash flow are very important to the capital markets. This specific question also yields significant tension as fair value accounting could be hypothesized to have a positive relationship with forecasting outcomes, no relationship with forecasting outcomes, or even a negative relationship with forecasting outcomes. Several competing reasons could impact any relationship between fair value asset holdings and the accuracy of analyst forecasts.

Our results documented herein appear to support several of the explanations for a relationship between fair value asset holdings and analyst forecast accuracy. Overall, we find a positive relationship between fair value asset holdings and forecast accuracy. However, this relationship does not hold for financial industry firms, suggesting that qualitative differences concerning the fair value assets themselves may be driving the real impact. Our results also indicate that it is fair value assets that are easiest to price (i.e., SFAS No. 157 Levels 1 and 2 assets) that have the most profound positive impact on forecasting outcomes. In addition, we also document that analyst bias is reduced by fair value measurements and that the financial crisis had a large impact on the relationship between fair value measurements and forecast accuracy for financial industry firms. In aggregate, these results suggest that a number of factors contribute to the relationship between fair value measurements and analyst forecast properties.

In different ways, our findings both dispute and support the findings of Magnan et al. (2015). They primarily attribute their main findings to

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an enhanced information environment brought about by the inception of SFAS No. 157. However, this period of time is heavily confounded by the financial crisis of the late 2000's. We find similar results for financial industry firms during that period of time, but those results change dramatically in the period following the crisis. We posit that our differences from Magnan et al. (2015) are most likely the product of the qualitative differences in the holding purposes and ultimate accounting treatments of these types of measurements for financial industry versus non-financial industry firms. One limitation of our study is that we cannot conclusively say that this is the case, even though evidence exists. Future research could possibly settle this issue with access to more descriptive data. We conclude by calling for more research in this important area.

Appendix A. Terms and definitions

$ACCURACY_{it}$ The absolute value of the difference between Firm *i*'s IBES median forecasted earnings per share and actual reported earnings per share as of time *t*, scaled by Firm *i*'s year-end stock price. Multiplied by negative one to produce positive coefficients for increases in accuracy.

$FV\_INTENSITY_{it}$ Firm *i*'s total combined dollar value of fair value assets (Compustat variables *aqpl1*, *aol2, and aul3*) and fair value liabilities (Compustat variables *lul3*, *lqpl1*, and *lol2*), scaled by the book value of Firm *i*'s total assets (Compustat variable *at*) as of time *t*.

$SIZE_{it}$ Firm i's natural logarithm of total assets (Compustat variable *at*) as of time *t*.

$LOSS_{it}$ A dichotomous variable equal to 1 if Firm *i*'s net income was less than zero for the period ended *t*; equal to zero otherwise.

$EARN\_VOLATILITY_{it}$ The standard deviation of Firm *i*'s return on assets (Compustat variable *ni* divided by Compustat variable *at*) for the previous five years.

$LEVERAGE_{it}$ Firm *i*'s interest bearing debt (Compustat variables dlc and dltt combined) divided by total assets (Compustat variable *at*), as of time *t*.

$MKTBK_{it}$ Firm *i*'s market value of equity (Compustat variable *mkvalt*) and liabilities (Compustat variable *lt*) divided by the book value of equity (Compustat variable *ceq*) and liabilities (Compustat variable *lt*), as of time *t*.

$SEGMENTS_{it}$ Firm *i*'s number of business segments from the Compustat Historical File, as of time *t*.

$EARN\_MOMENTUM_{it}$ The absolute value of the difference between current earnings per share (as of time *t*) and the prior year's earnings per share for Firm *i*, scaled by lagged stock price.

$FOLLOWING_{it}$ The number of unique analysts following Firm *i*, as of time *t*.

$LVL\_ONE\_INTENSITY_{it}$ Firm *i*'s total dollar value of SFAS No. 157 Level 1 assets (Compustat variable *aqpl1*) and liabilities (Compustat variable *lqpl1*), scaled by the book value of Firm *i*'s total assets (Compustat variable *at*) as of time *t*.

$LVL\_TWO\_INTENSITY_{it}$ Firm *i*'s total dollar value of SFAS No. 157 Level 2 assets (Compustat variable *aol2*) and liabilities (Compustat variable *lol2*), scaled by the book value of Firm *i*'s total assets (Compustat variable *at*) as of time *t*.

$LVL\_THREE\_INTENSITY_{it}$ Firm *i*'s total dollar value of SFAS No. 157 Level 3 assets (Compustat variable *aul3*) and liabilities (Compustat variable *lul3*) scaled by the book value of Firm *i*'s total assets (Compustat variable *at*) as of time *t*.

$BIAS_{it}$ The difference between Firm *i*'s IBES median forecasted earnings per share and actual reported earnings per share as of time *t*, scaled by Firm *i*'s year end stock price.

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