Analyst Conservatism in Poor Information Environments: The Effect on Earnings Management and the Likelihood of Meeting or Beating the Analyst Consensus

ABSTRACT

Conservative analysts react more to negative news than positive news, and the market response is greater for forecast revisions from conservative analysts, specifically in poor information environments (Hugon and Muslu, 2010; Keskek and Tse, 2018). While market participants have been shown to respond more to conservative analysts in poor information environments, little is known about how firms and managers respond to having a more conservative analyst following. We examine the effect of analyst conservatism on both accrual-based earnings management and the likelihood of meeting or beating the consensus forecast. Consistent with conservative analysts having a greater monitoring effect on managers, we find that firms in poor information environments with more conservative analyst followings engage in less income-increasing accrual-based earnings management. These results are stronger when analyst conservatism is easier for managers to identify. We also find that firms with a more conservative analyst following are more likely to meet or beat the consensus analyst forecast. Conservative analysts issue relatively lower earnings forecasts in response to both good and bad news, resulting in benchmarks which are easier for firms to meet or beat.

Keywords: Analyst conservatism, earnings management, analyst forecasts, information environment

JEL Classifications: G14, G24, M40, M41.

I. INTRODUCTION

On average, security analysts react more to positive news than negative news when revising their earnings forecasts (Easterwood and Nutt, 1999). Analysts who deviate from this trend and exhibit a greater reaction to negative news than positive news are deemed conservative. Market participants value the forecasts of conservative analysts more than other forecasts, as evidenced by a greater market reaction to earnings forecast revisions from conservative analysts relative to forecast revisions from other analysts (Hugon and Muslu, 2010). A firm's information environment is an important factor when considering the value of analyst conservatism, as analyst forecast properties differ in different information environments. Analysts are more pessimistic in rich information environments, where forecast dispersion and uncertainty about firm information are low, resulting in more positive earnings surprises. In poor information environments, where forecast dispersion and uncertainty about firm information are high, analyst forecasts are more optimistic on average (Tse and Yan, 2008). The stronger market reaction to conservative analyst forecast revisions is only evident in the poor information environment, where the average analyst issues more optimistic forecasts (Keskek and Tse, 2018). Thus, the value of a conservative analyst—who responds more to negative news than positive news—is greatest when the information environment is poor and the conservative analyst acts contrary to the average optimistic analyst in that environment. While the value of analyst conservatism to investors has been documented in a stronger return response to revisions in poor information environments, little is known about how managers and firms respond to analyst conservatism. In this study, we investigate the impact of analyst conservatism on earnings management behavior in poor information environments.

There are two potential main effects through which analysts can impact managers' decision making. Jensen and Meckling (1976) suggest that analysts can reduce the agency costs associated with the separation of ownership and control if they are effectively able to monitor managerial behavior. To the extent that analysts serve as external monitors of management, analyst following should be associated with less earnings management (the monitoring effect). Alternatively, if having an analyst following creates additional pressure for managers, a greater analyst following could be associated with more earnings management (the pressure effect). Yu (2008) finds that as the number of analysts following a firm increases, accrual-based earnings management decreases, consistent with the monitoring effect dominating the pressure effect as the number of analysts increases. Analyst conservatism in a poor information environment may magnify this dynamic, by simultaneously increasing the monitoring effect and decreasing the pressure effect. By definition, conservative analysts respond more to negative news than positive news. If a firm experiences good news, conservative analysts will respond with smaller upward forecast revisions, resulting in a relatively lower benchmark which is easier for the firm to achieve. Alternatively, if a firm experiences bad news, conservative analysts will respond with larger downward revisions on average, which similarly results in a relatively lower benchmark. In either scenario, there is potentially less pressure for the manager to manage earnings in order to meet a relatively lower benchmark, reducing the pressure effect. The monitoring effect is enhanced as the conservative analyst serves a greater monitoring role by virtue or reacting more to negative news than positive news. Thus, with the potential impact of both increasing the monitoring effect and decreasing the pressure effect, we examine earnings management and the likelihood of meeting or beating the consensus forecast of firms with more conservative analyst followings.[1]

[1] One potential concern with the effect of analyst conservatism on earnings management is how it may affect the walkdown phenomena, where analysts tend to revise their earnings forecasts down from the beginning to the end of

This paper is partially motivated by Beyer et al. (2010), who conclude (emphasis added):

> Researchers must consider the *interactions* between and among the objectives of *firms*, *managers*, regulators, *analysts*, investors, and other market participants as well as the incentives faced by these participants in determining the *information environment* observed in equilibrium…Additionally, the empirical earnings management literature investigating managers' attempts to *meet or beat* outstanding expectations assumes that analysts do not (or cannot) undo any effects of *earnings management*. (p. 335)

In other words, the related research to date has not simultaneously considered the joint dynamic between management behavior, analyst characteristics, and the information environment. Investors value information contained in earnings forecast revisions of conservative analysts in poor information environments (Keskek and Tse, 2018). That finding involves both analyst characteristics and the information environment, but does not consider firm or management behavior. Accordingly, our objective is to examine firm and manager behavior while jointly considering both analyst characteristics and the information environment. Specifically, we investigate both accrual-based earnings management and the likelihood of meeting or beating the consensus forecast for firms followed by conservative analysts in poor information environments.

A key component to our study is the measure of analyst conservatism, developed in Hugon and Muslu (2010). This measure is calculated annually for each individual analyst by comparing

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the forecasted period (quarter or year). The concern would be that conservative analysts could engage in less walkdown behavior, a potential explanation for why firms with more conservative analysts engage in less income-increasing accruals earnings management. In untabulated analysis, we find that there is no difference in the walkdown phenomena among firms with more conservative analysts relative to firms with less conservative analysts. We also examine this in the different information environments, finding a greater walkdown in poor information environments on average, but no difference due associated with analyst conservatism in either information environment.

each of an analyst's forecasts to forecasts of other analysts *following the same firm*.[2] Analysts identified as conservative are those that, across all the firms they follow, respond with larger downward forecast revisions for negative news relative to their upward forecast revisions for positive news than the other analysts following the same firms. We then create a firm-year level of analyst conservatism as the mean of the individual conservatism scores of all the analysts following the firm that year. Thus, a firm with a more conservative analyst following has a higher concentration of analysts who respond more to negative news than positive news. The potential implications for a firm with a more conservative analyst following are relatively lower earnings benchmarks that firms are more likely to meet or beat or that require less earnings management to achieve.

To test whether firms in poor information environments with more conservative analyst followings engage in less income-increasing earnings management, we regress signed discretionary accruals on analyst conservatism and relevant controls. We also test whether these firms are more likely to meet or beat the consensus forecast using a logistic regression. We obtain our data from IBES, CRSP, and Compustat, and construct our sample over the period 1990-2016. We use the Kothari et al. (2005) model to estimate discretionary accruals.[3] We utilize the measure of analyst conservatism from Hugon and Muslu (2010) discussed above. We identify the poor information environment based on analyst forecast dispersion.

We find that firms in poor information environments with more conservative analyst followings engage in less accrual-based earnings management. This suggests that analyst

[2] A benefit of this measure is that the conservatism is relative to other analysts following the same firm. If conservative analysts all select to follow the same firms, this measure captures the most conservative of those analysts. Section 3.2 discuss this further.

[3] While we present results using the performance adjusted discretionary accruals model from Kothari et al. (2005), results are qualitative similar when using the Jones (1991), Modified Jones, or Ball and Shivakumar (2006) models for estimating discretionary accruals.

conservatism not only impacts investors through stronger stock return responses to forecast revisions, but also impacts management behavior in poor information environments. These results are consistent with managers responding to a stronger monitoring effect of conservative analysts. To examine whether the negative association between analyst conservatism and accruals-based earnings management is driven by firms engaging in less income-increasing earnings management or more income-decreasing earnings management, we separately test observations with positive and negative discretionary accruals. We find that a more conservative analyst following is associated with both less income-increasing discretionary accruals and more income-decreasing discretionary accruals. In other words, firms with conservative analyst followings are less likely to manage earnings up and more likely to manage earnings down. We also separately test firms experiencing good news and bad news (based on annual stock returns), because conservative analysts respond with larger downward revisions to bad news than upward revisions in response to good news. We find the negative association between analyst conservatism and accruals-based earnings management in both settings, consistent with a lower benchmark necessitating less earning management for either good or bad news. We also find that the results relating to accruals-based earnings management are stronger in settings where analyst conservatism is easier for managers to identify (when the firm has a smaller analyst following or when the analysts following the firm issue fewer forecasts).

We also consider a firm’s tendency to meet or beat earnings benchmarks. We find that analyst conservatism is associated with an increased likelihood of meeting or beating the analyst consensus. These results appear to be driven by firms experiencing bad news, as conservative analysts respond with larger downward revisions to bad news, resulting in a relatively lower earnings benchmark. The results relating to meeting or beating earnings are stronger when the firm has a larger analyst following or analysts following the firm issue more forecasts. Both the accruals-based earnings management findings and the meet or beat findings are materially unchanged when utilizing an entropy-balanced sample or a propensity score matching approach.[4]

This study makes multiple contributions. First, while other studies have separately examined associations between analyst characteristics and management behavior or analyst characteristics and information environment, this is the first study to our knowledge that has simultaneously considered the impact of analyst characteristics and the information environment on management behavior, answering the call from Beyer et al. (2010). In doing so, we provide evidence that the characteristics of the analysts following a company are associated with management and firm behavior in a poor information environment. Specifically, managers in poor information environments respond to conservative analysts by engaging in less accruals-based earnings management. This provides incremental evidence from a unique context to the information environment literature. Second, prior literature has documented that analyst conservatism can impact the market's reaction to their forecast revisions. We advance this literature by demonstrating that analyst conservatism can also impact management and firm behavior. Finally, we add to the analyst forecast literature by illustrating that the likelihood of a firm achieving an earnings target is greater for firms in poor information environments with more conservative analyst followings. While these managers engage in less accruals-based earnings management, they are more likely to meet or beat the consensus earnings targets, presumably because conservative analysts tend to provide lower targets via smaller upward revisions to good

[4] In untabulated analyses, we perform entropy balancing and propensity score matching (PSM). We do this because a potential concern is that the results we find in the poor information environment are instead due to the differences between poor and rich information environments that are not related to analyst conservatism. Our results continue to hold under both entropy balancing and propensity score matching approaches.

news and larger downward revisions to bad news.

II. BACKGROUND AND HYPOTHESES

Analysts

Security analysts play a vital role in the facilitation of capital markets. Analysts follow a finite number of firms and generally specialize within a few industries. An analyst following a firm will perform research on the firm, participate in conference calls, and issue earnings forecasts. Multiple analysts follow a firm, and the consensus forecast for a firm combines all analyst forecasts for that firm. As the earnings announcement date draws closer, analysts often revise their estimates upward or downward as more information becomes available to them. If the volume and quality of information about a firm is high, analysts' forecasts will tend to be relatively similar to one another, compared to cases where information is lacking or uncertain. Thus, the amount of dispersion in analyst forecasts is indicative of uncertainty in the information environment (Barron et al. 2009; Barron and Stuerke 1998; Barron et al. 1998). Increased levels of information enable analysts to forecast company performance more consistent with one another, which leads to forecasts that are more tightly clustered with reduced outliers. Barron and Stuerke (1998) find a positive relation between forecast dispersion and informational demand, consistent with dispersion in analysts' earnings forecasts serving as a useful indicator of uncertainty about future performance.

The importance of individual analysts has been considered in the literature. Kirk, Reppenhagen, and Tucker (2014) document that investors may at times rely on individual analyst forecasts rather than the consensus forecast because the consensus forecast de-values (i.e., averages out) private information contained in individual forecasts. Analysts with forecasts that are relatively more useful have been referred to as "influential analysts." Zhou (2019) finds that when an influential analyst disagrees with the consensus, managers are more likely to act in accordance with the influential analyst. Additionally, less influential analysts prefer to stay away from influential analysts. Luo, Yin, and Zhang (2019) document that "non-star analysts" prefer to avoid competing with "star analysts," and adjust their coverage accordingly; in doing so, these non-stars often end up benefiting later in their careers. Overall, prior research shows that analysts add value in the capital markets (Healy and Palepu 2001) and that firms followed by more analysts tend to manage earnings less (Yu 2008). However, other characteristics of analysts (i.e., conservatism) may elicit different responses from firm management.

Forecast Bias

Generally, analysts have been found to react more to positive news than to negative news (Easterwood and Nutt, 1999), and often exhibit bias in their earnings forecasts in order to promote their own self-interest, frequently related to their career aspirations. Specifically, an analyst may want to curry favor with an investment bank for future career advancement or longevity, or curry favor with the company's management in order to be treated favorably in the future (e.g., be given more attention on earnings calls). O'Brien et al. (2005) find that analysts affiliated with investment banks are relatively quick to upgrade their stock recommendations, yet slow to downgrade stock recommendations, suggesting that this affiliation makes analysts hesitant to convey negative news. Cowen et al. (2006) find that analysts employed by firms that engage in underwriting activities tend to make less optimistic forecasts than analysts employed by brokerage houses not performing underwriting. This could be due to currying favor with management (and earning their business in the future) by enabling them to achieve a lower earnings target. Brokerage houses appear to enhance the careers of analysts with optimistic forecasts, so long as the analysts are relatively accurate (Hong and Kubick, 2003).

Analysts who initially issue optimistic forecasts and subsequently walk them down as the earnings announcement date approaches tend to have better job security, presumably because this can curry favor with management by better enabling management to meet expectations (Cotter, Tuna, and Wysocki, 2006; Ke and Yu, 2006). It is possible that such forecast walkdown findings are not entirely due to analyst opportunism. Richardson, Teoh, and Wysocki (2004) find results that suggest that management may behave in an opportunistic manner by guiding analysts' forecasts downward in order to realize larger gains when selling their stock holdings after releasing earnings that beat expectations. The forecast walkdown phenomenon is also related to forecast difficulty. Bradshaw, Lee, and Peterson (2016) find that analyst forecast walkdowns are not solely motivated by analyst incentives, but are also due in part to forecasting difficulty, and the interaction between incentives and difficulty. There are other intricacies to be considered as well. For instance, Horton, Serafeim, and Wu (2017) investigate banking analysts, and find that forecast walkdowns are more likely to be observed when the analyst is reporting on a potential future employer.

In rich information environments, earnings forecasts are typically lower, and thus, increase the likelihood of a positive earnings surprise; alternatively, in poor information environments, earnings forecasts are typically higher, increasing the likelihood of a negative earnings surprise (Tse and Yan, 2008). Tse and Yan (2008) suggest that analysts appear to benefit in their careers by being pessimistic in rich information environments, as this increases the likelihood of a positive earnings surprises, which is valued by companies and investment banks. In the pre-Reg FD period, when non-public information was needed to accurately forecast earnings, analysts issued more optimistic forecasts in order to appease management and receive access to non-public information in the future (Das et al., 1998).

Other instances of analyst bias may be less self-serving. Analysts forecasts may be partially driven by past macroeconomic conditions. Clement and Law (2014) find that analysts that start their career during a recession tend to be more conservative, in the sense that they are more pessimistic, less likely to differ from consensus, and more (less) likely to issue negative (positive) forecast revisions. Analysts may also suffer from first impression bias. Hirshleifer et al. (2019) find that if a company performs quite well (poorly) in the year preceding an analyst following the company, that analyst tends to be optimistic (pessimistic) in forecasting future performance, relative to other analysts. Analysts have been noted to adjust their forecasts based on the firm's ownership structure. Charitou et al. (2019) find analysts tend to increase (decrease) their forecast horizons when the company is owned by investors with long-term (short-term) investment horizons. Whatever the reason, some analysts tend to behave in a more biased manner than others.

Conservative Analysts

Given the nature of potential analyst bias discussed, it is no surprise that the literature has developed a definition for conservative analysts: analysts "who generate more informative forecasts by unwinding, at least in part, the aggressive research practices representative of analysts more generally" (Hugon and Muslu 2010, 43). Hugon and Muslu (2010) develop a measure of analyst conservatism and find that the market reaction to analyst forecast revisions is stronger for conservative analysts. In this paper, we examine whether managers respond to the level of conservative analysts following their firms. To address this, we examine an earnings management context, as analyst conservatism may impact managers' perceptions of the need to management earnings.

The Hugon and Muslu (2010) model is designed to be "conditional (based on an individual analyst's reactions to news direction, bad versus good) and relative (based on an individual analyst's reactions relative to those of peer analysts)" (Hugon and Muslu 2010, 43). The model allows the level of a given analyst's conservatism to change from year to year, depending on forecast revisions made each year. Hugon and Muslu (2010) show that conservative analysts have more experience, work for larger investment houses, are Institutional Investor award winners, and issue forecasts that are more persistent (i.e., more predictive of future earnings revisions) and more accurate. This paper examines how a more conservative analyst following can influence managerial and firm financial reporting behavior.

Keskek and Tse (2018) find that the stronger market reaction to forecast revisions from conservative analysts originally documented in Hugon and Muslu (2010) is only significant in poor information environments (where analyst forecast dispersion is greater). In other words, Keskek and Tse (2018) find that investors anticipate and combat biased analysts by reducing their response to upward (downward) forecast revisions in poor (rich) information environments. Thus, it appears that when information is lacking, investors do not put much faith into positive forecast revisions from analysts; and when information is plentiful, investors are not shocked by downward revisions. Furthermore, there is a stronger market response to forecast revisions of conservative analysts, but only in poor information environments (which tend to be full of optimistic bias).

Accordingly, we also consider the impact of the information environment in the relation between conservative analysts and management behavior (earnings management).

Hypotheses

Earnings management occurs when managers make changes to the estimates of their discretionary accrual accounts, resulting in a temporary effect on account balances, or make policy changes resulting in a permanent effect on account balances. There are two potential main effects through which analysts can impact the decision making of managers: the monitoring effect and the pressure effect. By serving as external monitors, analysts can reduce agency costs and curb aggressive management behavior (Jensen and Meckling, 1976). The monitoring effect predicts that to the extent that analysts serve as external monitors of management, analyst following should be associated with less earnings management. The pressure effect predicts that analysts create additional pressure for managers, and that a greater analyst following would be associated with more earnings management. Yu (2008) provides evidence that the monitoring effect dominates the pressure effect as analyst following increases.

Analyst conservatism could potentially affect both the monitoring and pressure effects. By definition, conservative analysts respond more to bad news than good news, meaning smaller upward forecast revisions in response to good news and larger downward forecast revisions in response to bad news. Thus, the resulting consensus earnings forecast is relatively lower for firms with a more conservative analyst following in either the good news setting or bad news setting. This lower benchmark suggests that: (1) managers have less need to manage earnings in order to meet the benchmark and (2) firms would be more likely to meet or beat the relatively lower target. In other words, the monitoring effect increases due to conservative analysts responding more negatively to bad news, and the pressure effect decreases due to a relatively easier benchmark to achieve. Because the stronger market reaction to conservative analysts exists only in poor information environments (Keskek and Tse 2018), we predict these effects of analyst conservatism will occur in poor information environments. Accordingly, we state our hypotheses as follows:

H1: In poor information environments, the conservatism of the firm's analyst following is *negatively* associated with *accruals-based earnings management*.

H2: In poor information environments, the conservatism of the firm's analyst following is *positively* associated with *meeting or beating the consensus analyst forecast*.

III. DESIGN

Sample

Our sample begins with all Compustat firm-year observations from 1990 to 2016. As is standard practice, we exclude firms in the financial and utilities industries (SIC code 4400-4999 and 6000-6999, respectively) due to differing reporting incentives. We exclude firm-years with insufficient data to estimate the discretionary accruals model, as well as those without IBES coverage. We require that each firm-year observation have at least three analysts providing earnings per share ("EPS") forecasts for that year so that inferences about conservative analysts are not skewed by observations with only one or two analysts. After excluding observations with missing control variables, our full sample consists of 34,281 firm-year observations. The focus of our analyses is the poor information environment, defined as the highest tercile of analyst forecast dispersion, resulting in a final sample of 11,427 firm-year observations. All continuous variables are winsorized at the 1st and 99th percentiles. See Table 1 for more detail on our sample selection process.

Measure of Analyst Conservatism

Conceptually, a conservative analyst is one that, relative to analyst peers, responds asymmetrically more to negative news about a firm than to positive news. We follow the methodology of Hugon and Muslu (2010) – which is constructed in a manner consistent with that of conservative financial reporting per Basu (1997) – to calculate an analyst-year measure of conservatism. We estimate the following regression for each analyst-year, using all forecasts issued by the analyst in that calendar year for all firms followed:[5]

$$REV_{i,j,t} = \alpha_0 + \alpha_1 BADNEWS_{N,j,t} + \beta_0\, REV_{N,j,t} + \beta_1\, BADNEWS_{N,j,t} \times REV_{N,j,t} + \varepsilon_{i,j,t} \qquad (1)$$

where:

$REV_{i,j,t}$	=	analyst *i*'s earnings forecast revision, calculated as analyst *i*'s forecast of year *t* earnings for firm *j* minus the mean consensus forecast for firm *j*, scaled by the preceding monthly stock price. The mean consensus forecast is based on all forecasts issued in the 30 days prior to the forecast of the nearest neighbor analyst prior to analyst *i*.
$REV_{N,j,t}$	=	average revision of analyst *i*'s closest two neighbors (one preceding and the other succeeding analyst *i*), where each revision is calculated as the neighboring analyst's forecast for firm *j* minus the mean consensus forecast for firm *j*, scaled by the preceding monthly stock price.
$BADNEWS_{N,j,t}$	=	a bad news indicator, equal to 1 when $REV_{N,j,t} < 0$ and equal to 0 when $REV_{N,j,t} \geq 0$.

An individual analyst's conservatism is calculated as the ratio of their response to bad news versus good news, $(\beta_0 + \beta_1)/\beta_0$. Following Keskek and Tse (2018), if β_0 is less than 0.1, we scale $(\beta_0 + \beta_1)$ by 0.1 rather than β_0 to avoid large conservatism values due to a small denominator.[6] In line with Hugon and Muslu (2010), we require (1) that each analyst make at least eight forecast

[5] This estimation is done out of sample, using all forecasts issued by the analyst during the year, even if the firms being followed are not in our final sample in order to capture the analyst's forecasting conservatism that year.

[6] Our results are similar if we use Hugon and Muslu (2010)'s original measure and do not replace β_0 with 0.1 in calculating the conservatism measure.

revisions in a calendar year, including at least two upward revisions and two downward revisions, (2) that neighbor analysts' revisions must be issued within one week before or after analyst i's revision, (3) that analysts respond positively to good news ($\beta_0 > 0$) and (4) we exclude forecast revision observations with absolute Studentized residuals greater than three to remove outliers. We then quintile rank this conservatism measure within each year to calculate a measure of analyst conservatism, *CONSERV_ANALYST*, for each analyst-year.

Earnings Management

We test whether firms with more conservative analyst followings are associated with lower levels of accruals-based earnings management by estimating the following regression, with performance-adjusted discretionary accruals as the dependent variable (Kothari et al., 2005):

$$DACC_{i,t} = \beta_0 + \beta_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \beta_n Controls_{i,t} + \beta_j IndustryFE + \beta_k YearFE + \varepsilon_{i,t} \quad (2)$$

Our variable of interest, $AVG\_CONSERV\_ANALYST_{t-1}$, is the average conservatism quintile rank (*CONSERV_ANALYST*) in year t-1 of all the analysts that issued a forecast for firm i in year t. Because Equation (1) is estimated based on calendar years and the conservatism of analysts in a given year may not be known prior to a firm's fiscal year end, we examine the association between analyst conservatism in year t-1 with firm behavior in year t.[7] This also allows managers to potentially recognize the conservatism of the analysts following their firm and respond accordingly. We predict a negative β_1 coefficient, indicating firms with more conservative analysts engage in less income-increasing (or more income-decreasing) earnings management. Keskek and Tse (2018) find that the stronger market reaction to forecast revisions from

[7] This is consistent with Hugon on Muslu (2010), who examined the market reaction to forecasts in year t based on conservatism in year t-1 ($CONSERV_{t-1}$).

conservative analysts originally documented in Hugon and Muslu (2010) is only significant in poor information environments, where analyst forecast dispersion is greater. Thus, we focus our tests on the poor information environment, proxied by firm-years in the highest tercile of analyst forecast dispersion.

One potential concern of endogeneity with our measure is that more conservative analysts may choose to follow firms that are less likely to engage in income-increasing earnings management. Fortunately, the calculation of analyst conservatism addresses this issue. The annual conservatism of an individual analyst is calculated by comparing each of the analyst's forecasts to forecasts of other analysts *following the same firm*, i.e., each observation used in estimating Equation (1) utilizes a comparison of forecasts issued by different analysts for a single firm. Thus, analysts identified as conservative in a given year are those that respond more to negative news across all the firms they follow, relative to other analysts following the same firms. Thus, the firm-years with higher values of *AVG_CONSERV_ANALYST* have a higher concentration of analysts who respond more to negative news than their analyst peers across all followed firms. If there were two contingents of analysts who follow two distinct groups of firms (i.e., "conservative" analysts follow "conservative" firms and "aggressive" analysts follow "aggressive" firms), the conservatism measure would identify the more conservative analysts within each contingent due to the relative nature of the calculation rather than identifying only the conservative contingent.

We control for firm characteristics including firm size (*SIZE*), return on assets (*ROA*), leverage (*LEVERAGE*), loss firms (*LOSS*), and the book-to-market ratio (*BTM*). Because a firm’s ability to manage through accruals is constrained by prior estimates reflected on the balance sheet (Barton & Simko 2002), we include the firm’s level of net operating assets (*NOA*). We also control for institutional ownership (*INSTOWN*) and the presence of a Big N auditor (*BIG4*). We include several analyst-related control variables, including the number of analysts following the firm (*NUMANALYSTS*), the average number of years of forecasting experience of the analysts following the firm (*AVG_TOTALEXPERIENCE*), the average number of years of firm-specific forecasting experience (*AVG_FIRMEXPERIENCE*), the average number of firms followed (*AVG_FIRMSFOLLOWED*), the average number of forecasts issued during the year for all firms (*AVG_TOTALFORECASTS*), and the average size of the analyst's brokerage (*AVG_BSIZE*). Finally, we include industry and year fixed effects to control for any industry or year specific trends in managing earnings.

Meeting or Beating Consensus Analyst Forecast

We also test whether firms with more conservative analyst followings are associated with a higher likelihood of meeting or beating the consensus analyst forecast by estimating the following logistic regression:

$$MB_{i,t} = f(\alpha_0 + \alpha_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \alpha_n Controls_{i,t} + \alpha_j IndustryFE + \alpha_k YearFE + \varepsilon_{i,t}) \quad (3)$$

MB is one of two variables (*MBE* or *BEAT*) related to meeting or beating the consensus forecast. *MBE* is an indicator variable equal to one if the actual EPS is greater than or equal to the consensus analyst forecast, and zero otherwise. *BEAT* is an indicator variable equal to one if the actual EPS is greater than the consensus, and zero otherwise. The difference in these two measures is the treatment of firm-year observations where the actual EPS is equal to the consensus. We predict that α_1 will be positive, indicating that firms with more conservative analyst followings will be associated with a higher likelihood of meeting or beating the consensus forecast. Control variables are the same as those in Equation (2).

IV. RESULTS

Descriptive Statistics

Panel A of Table 2 reports descriptive statistics for the sample of 34,281 firm-year observations. Panel B Table 2 presents descriptive statistics for the poor information environment (defined as the highest tercile of analyst forecast dispersion), the sample used for the majority of our tests, consisting of 11,427 firm-year observations. The average $AVG\_CONSERV\_ANALYST_{t-1}$ in the poor information environment sample is 2.05, indicating an average conservatism of analysts following the firm in the middle quintile of conservatism (on a scale of zero to four). The descriptive statistics also reveal that there are firm-years where all the analysts following the firm are in the highest quintile ($AVG\_CONSERV\_ANALYST_{t-1}$ = 4) and other firm-years where all the analysts are in the lowest conservatism quintile ($AVG\_CONSERV\_ANALYST_{t-1}$ = 0).

Regression Results

Table 3 reports results of our estimation of Equation (2) for the full sample (Column 1) and the poor information environment (Column 2). We do not find a significant association between conservative analyst following and discretionary accruals in the full sample. This result is not surprising given the findings of Keskek and Tse (2018) that the stronger market response to conservative analysts only occurs in poor information environments. Consistent with H1, we find that the coefficient on $AVG\_CONSERV\_ANALYST_{t-1}$ is negative and significant in the poor information environment, suggesting that when there is less consensus among analysts (i.e., more forecast dispersion), firms with more conservative analysts engage in less accruals-based earnings management.[8] A potential explanation for this finding is a lower earnings benchmark as a result of

[8] In untabulated analysis, we find no significant association between $AVG\_CONSERV\_ANALYST_{t-}$ and *DACC* in the rich information environment (lowest analyst forecast dispersion tercile).

conservative forecast revisions requiring less earnings management, consistent with a stronger monitoring effect.

The negative association we find between the conservatism of a firm's analyst following and accruals-based earnings management could be due to managers engaging in less income-increasing earnings management, managers engaging in more income-decreasing earnings management, or both. We do not make a separate prediction regarding income-increasing or income-decreasing earnings management, but do examine these difference explanations in Table 4. We separately estimate Equation (2) using firm-year observations with positive discretionary accruals and firm-year observations with negative discretionary accruals, and present results in Columns 1 and 2. For ease of interpretation in the negative discretionary accruals column (and only for that column), we multiply *DACC* by negative 1 so that higher values represent more income-decreasing earnings management. We find that firms with more conservative analyst followings have both lower income-increasing discretionary accruals and high income-decreasing discretionary accruals. In other words, managers with more conservative analyst followings manage earnings up less and manage earnings down more, as compared to firms followed by less conservative analysts. The coefficient magnitude and significance are higher in the positive discretionary accruals subsample, indicating that our main results are driven more by firms followed by more conservative analysts engaging in less income-increasing earnings management. Firms with lower earnings benchmarks as a result of conservative forecast revisions would need to engage in less income-increasing earnings management in order to meet that benchmark.

Additionally, a lower benchmark would be more easily achieved, allowing managers of firms that sufficiently met the benchmark to manage earnings down in order to create “cookie jar” reserves.

Conservative analysts respond with larger downward revisions to negative news relative to their upward revisions to good news. Although the ultimate effect in both good news or bad news settings is a relatively lower consensus forecast, we separately examine settings where the firm experiences good or bad news, based on the annual stock return. We present results of estimating Equation (2) in both good news and bad news subsamples in Columns 3 and 4 of Table 4. We find a negative and significant coefficient on $AVG\_CONSERV\_ANALYST_{t-1}$ in both subsamples, indicating that the negative association between analyst conservatism and accruals-based earnings management is not dependent on the type of news the firm experiences.

Table 5 presents the results of estimating Equation (3) in the poor information environment with *MBE* (meet or beat) as the dependent variable in Panel A, and *BEAT* (beat only) as the dependent variable in Panel B.[9] Consistent with H2, we find a positive and significant coefficient on $AVG\_CONSERV\_ANALYST_{t-1}$ with both dependent variables, suggesting that firms followed by more conservative analysts are more likely to meet or beat the consensus analyst forecast. This result supports a reduction in the pressure effect, due to a lower and more easily attainable earnings benchmark from conservative forecast revisions. Similar to the discretionary accruals analysis, we separately examine good news and bad news settings. We find that the results are driven by firms experiencing bad news, where conservative analysts would respond with larger downward forecast revisions. This result is consistent with conservative analysts having a stronger effect on the consensus, and ultimately the firm’s ability to meet or beat the consensus when forecasting

[9] Consistent with our discretionary accruals results in the full sample (all information environments), in untabulated analysis we find no difference in the likelihood of meeting or beating the consensus forecast based on the conservatism of a firm’s analyst following in the full sample (all information environments).

contrary to the average optimistic analyst in a poor information environment. Results with *BEAT* as the dependent variable in Panel B are similar in sign and significance to results in Panel A with *MBE* as the dependent variable.

If managers are recognizing and responding to the conservatism of their analyst following, we would expect our accruals-based earnings management results to be stronger when managers have an easier time identifying analyst conservatism. Two settings where this may be the case are (1) when the analysts following the firm issue fewer forecasts, and (2) when the firm is followed by fewer analysts. If an analyst issues fewer forecasts, there is less information for the managers to process, so identifying more conservative analysts may be more salient to managers. Fewer analysts following the firm would mean less information to process, but it could also mean a stronger influence of a single conservative analyst. We examine both of these settings in Panel A of Table 6 by splitting the sample on the median size of analyst following and frequency of analyst forecasts. The significant results for small analyst followings and low forecast frequency suggest that managers respond to analyst conservatism by engaging in less accruals-based earnings management when analyst conservatism is more easily identifiable for managers.

The implications of splitting the sample based on following size and forecast frequency is different for the effect on the consensus and likelihood of meeting or beating the consensus. While the analyst conservatism measure is measured using all forecasts of an analyst in a year, any specific forecast of a conservative analyst for a given firm may not necessarily be conservative. However, as the number of conservative analysts following a firm increases, the likelihood of a conservative effect for a given firm increases, resulting in a lower consensus that is easier to meet or beat. Similarly, the influence of a single extremely conservative forecast could potentially classify an analyst as conservative in a given year if the analyst issues very few forecasts. Thus, the majority of an analyst's individual forecasts may not be conservative, but the analyst is classified as conservative due to a small number of forecasts. The influence of such outliers on a given analyst's conservatism classification decreases as the number of forecasts issued increases. Thus, as forecast frequency increased, the likelihood of a conservative analyst's forecast for a given firm being conservative increases, which would result in a lower consensus. Accordingly, we expect that effect of analyst conservatism on the consensus (i.e., reducing the consensus and making it more likely for firms to meet or beat) is greater when a firm's analyst following is larger or the analysts following a firm issue more forecasts. This is what we find in Table 6, Panels B and C, where firms followed by more conservative analysts are more likely to meet or beat the consensus forecast when analyst followings are large or forecast frequency is high.

V. CONCLUSION

While the stronger market reaction to conservative analyst forecast revisions has been documented in poor information environments, little is known about the influence of analyst conservatism on managerial or firm behavior. In this study, we investigate the impact of analyst conservatism on both accruals-based earnings management and the likelihood of meeting or beating the consensus analyst forecast in poor information environments.

We find that firms in poor information environments with more conservative analyst followings engage in less accruals-based earnings management, yet are more likely to meet or beat the consensus analyst forecast. We posit that the combination of these results is due to conservative analysts reacting with larger downward revisions to negative news, and smaller upward revisions to positive news, ultimately resulting in a lower earnings benchmark that is easier to achieve and requires less earnings management to do so. These effects are magnified in settings where analyst conservatism is easier for managers to identify, and when analyst conservatism is most likely to impact a given firm earnings forecast. Our results suggest that manager and firm behavior is associated not only with a specific analyst characteristic (conservatism), but also the information environment. We advance the literature by examining manager and firm behavior while simultaneously consider analyst characteristics and the information environment.

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Table 1: Sample Selection

	Firm-Year Observations
Compustat data from 1990 to 2016	213,667
Financials and Utilities (SIC codes 44-49 & 60-69)	(54,832)
	158,835
Missing data necessary to calculate discretionary accruals	(16,553)
	142,282
Missing IBES coverage	(61,005)
	81,277
Fewer than three analysts following the firm	(20,734)
	60,543
Missing control variables	(26,262)
Full Sample	**34,281**
Observations in bottom and middle terciles of analyst forecast dispersion	(22,854)
Poor Information Environment Sample	**11,427**

Table 1 presents the sample selection procedure.

Table 2: Descriptive Statistics

Panel A: Full Sample								
Variables	**N**	**Mean**	**S.D.**	**Min**	**25th**	**Med**	**75th**	**Max**
Dependent Variables								
DACC	34,281	-0.02	0.10	-0.38	-0.07	-0.02	0.03	0.33
MBE	34,281	0.64	0.48	0.00	0.00	1.00	1.00	1.00
BEAT	34,281	0.61	0.49	0.00	0.00	1.00	1.00	1.00
Independent Variables								
AVG_CONSERV_ANALYST$_{t-1}$	34,281	2.09	0.73	0.00	1.67	2.05	2.50	4.00
Control Variables								
SIZE	34,281	7.02	1.76	3.43	5.76	6.89	8.13	11.75
ROA	34,281	0.02	0.20	-1.10	0.01	0.06	0.11	0.42
LEVERAGE	34,281	0.21	0.19	0.00	0.02	0.18	0.33	0.84
LOSS	34,281	0.38	0.49	0.00	0.00	0.00	1.00	1.00
BTM	34,281	0.47	0.37	-0.23	0.22	0.38	0.61	2.09
NOA	34,281	0.64	0.37	-0.27	0.45	0.64	0.80	2.32
INSTOWN	34,281	0.58	0.29	0.00	0.37	0.62	0.80	1.16
BIG4	34,281	0.93	0.26	0.00	1.00	1.00	1.00	1.00
NUMANALYSTS	34,281	11.75	7.91	3.00	6.00	9.00	16.00	38.00
AVG_TOTALEXPERIENCE	34,281	4.94	1.98	1.22	3.50	4.75	6.17	10.60
AVG_FIRMEXPERIENCE	34,281	2.10	1.40	0.00	1.00	1.90	3.00	6.22
AVG_FIRMSFOLLOWED	34,281	14.94	4.34	5.00	12.20	14.57	17.18	30.29
AVG_TOTALFORECASTS	34,281	55.60	22.01	16.83	41.00	52.21	65.42	139.29
AVG_BSIZE	34,281	54.90	25.46	10.80	37.00	51.84	68.44	140.17

Panel A of Table 2 presents descriptive statistics for the full sample of firm-year observations from 1990-2016. Please refer to Table 1 for sample selection criteria and Appendix A for variable definitions.

Panel B: Poor Information Environment (High Analyst Forecast Dispersion)								
Variables	**N**	**Mean**	**S.D.**	**Min**	**25th**	**Med**	**75th**	**Max**
Dependent Variables								
DACC	11,427	-0.02	0.10	-0.38	-0.07	-0.02	0.03	0.33
MBE	11,427	0.56	0.50	0.00	0.00	1.00	1.00	1.00
BEAT	11,427	0.56	0.50	0.00	0.00	1.00	1.00	1.00
Independent Variables								
$AVG\_CONSERV\_ANALYST_{t-1}$	11,427	2.05	0.70	0.00	1.67	2.00	2.50	4.00
Control Variables								
SIZE	11,427	7.40	1.79	3.43	6.15	7.31	8.58	11.75
ROA	11,427	0.01	0.22	-1.10	-0.01	0.05	0.09	0.42
LEVERAGE	11,427	0.24	0.19	0.00	0.08	0.22	0.35	0.84
LOSS	11,427	0.41	0.49	0.00	0.00	0.00	1.00	1.00
BTM	11,427	0.51	0.40	-0.23	0.25	0.43	0.66	2.09
NOA	11,427	0.65	0.38	-0.27	0.46	0.64	0.79	2.32
INSTOWN	11,427	0.57	0.29	0.00	0.36	0.61	0.79	1.16
BIG4	11,427	0.95	0.22	0.00	1.00	1.00	1.00	1.00
NUMANALYSTS	11,427	13.89	8.49	3.00	7.00	12.00	19.00	38.00
AVG_TOTALEXPERIENCE	11,427	4.91	1.85	1.22	3.57	4.78	6.05	10.60
AVG_FIRMEXPERIENCE	11,427	2.26	1.40	0.00	1.18	2.13	3.19	6.22
AVG_FIRMSFOLLOWED	11,427	15.22	4.63	5.00	12.38	15.00	17.78	30.29
AVG_TOTALFORECASTS	11,427	60.13	25.76	16.83	43.21	55.09	71.00	139.29
AVG_BSIZE	11,427	56.52	24.20	10.80	40.17	53.15	68.72	140.17

Panel B of Table 2 presents descriptive statistics for the subsample of firm-year observations with a poor information environment, proxied by firm-year observations in the highest tercile of analyst forecast dispersion. Please refer to Table 1 for sample selection criteria and Appendix A for variable definitions.

Table 3: Accruals-Based Earnings Management

OLS Regression Results of Conservative Analysts on Discretionary Accruals

$$DACC_{i,t} = \beta_0 + \beta_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \beta_n Controls_{i,t} + \beta_j IndustryFE + \beta_k YearFE + \varepsilon_{i,t} \quad (2)$$

Variable	Predicted Sign	Full Sample	Poor Info. Environment
AVG_CONSERV_ANALYST$_{t-1}$	–	**-0.000**	**-0.003****
		(-0.266)	**(-2.090)**
SIZE		-0.008***	-0.007***
		(-9.651)	(-5.310)
ROA		-0.091***	-0.070***
		(-11.128)	(-5.590)
LEVERAGE		0.020***	0.023***
		(4.337)	(3.040)
LOSS		0.001	-0.000
		(0.530)	(-0.039)
BTM		0.009***	0.009***
		(3.964)	(2.735)
NOA		0.015***	0.004
		(4.387)	(0.814)
INSTOWN		-0.011***	-0.001
		(-3.605)	(-0.259)
BIG4		-0.004	-0.005
		(-1.277)	(-0.918)
NUMANALYSTS		-0.000	-0.000
		(-1.510)	(-1.581)
AVG_TOTALEXPERIENCE		-0.001	0.000
		(-1.201)	(0.239)
AVG_FIRMEXPERIENCE		0.002***	0.003**
		(2.939)	(2.368)
AVG_FIRMSFOLLOWED		0.001***	0.001***
		(4.494)	(3.284)
AVG_TOTALFORECASTS		-0.000***	-0.000***
		(-3.867)	(-3.718)
AVG_BSIZE		0.000	0.000
		(0.487)	(0.384)
Constant		0.018**	0.014
		(2.167)	(1.041)
Industry and Year FE		Yes	Yes
N		34,281	11,427
R^2		0.087	0.075

Table 3 presents regression results of estimating Equation (2). Estimated coefficients are presented with t-statistics in parenthesis below. Poor (rich) information environment is proxied by firm-year observations in the highest (lowest) tercile of analyst forecast dispersion. See Table 1 for sample selection and Appendix A for variable definitions. ***, **, and * indicate significance at the p<0.01, 0.05, 0.10 levels. Significance is one-tailed for associations with predicted signs and two-tailed otherwise.

Table 4: Signed Discretionary Accruals and News in Poor Information Environments

$$DACC_{i,t} = \beta_0 + \beta_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \beta_n Controls_{n,i,t} + \beta_j IndustryFE + \beta_k YearFE + \varepsilon_{i,t} \quad (2)$$

Variable	Predicted Sign	Positive DACC	Negative DACC	Good News	Bad News
AVG_CONSERV_ANALYST$_{t-1}$	**–**	**-0.004*****	**0.002***	**-0.003***	**-0.003***
	(+ for Neg *DACC*)	**(-2.469)**	**(1.421)**	**(-1.452)**	**(-1.378)**
SIZE		-0.006***	0.001	-0.008***	-0.006***
		(-5.827)	(0.734)	(-4.674)	(-4.294)
ROA		-0.098***	-0.073***	-0.092***	-0.016
		(-12.133)	(-7.129)	(-6.266)	(-0.768)
LEVERAGE		-0.043***	-0.070***	0.039***	0.019*
		(-6.999)	(-10.150)	(3.982)	(1.843)
LOSS		0.004*	0.008***	0.001	0.001
		(1.729)	(3.522)	(0.432)	(0.141)
BTM		-0.025***	-0.035***	0.022***	0.007**
		(-9.732)	(-12.020)	(3.814)	(2.048)
NOA		0.037***	0.022***	0.010	-0.014*
		(9.682)	(5.333)	(1.442)	(-1.874)
INSTOWN		-0.019***	-0.017***	-0.003	-0.003
		(-5.062)	(-4.058)	(-0.505)	(-0.502)
BIG4		-0.000	-0.001	-0.014*	0.003
		(-0.091)	(-0.230)	(-1.689)	(0.452)
NUMANALYSTS		-0.000	-0.000	-0.000	-0.000*
		(-1.368)	(-0.794)	(-0.367)	(-1.717)
AVG_TOTALEXPERIENCE		0.001	0.000	0.000	0.000
		(1.079)	(0.555)	(0.292)	(0.413)
AVG_FIRMEXPERIENCE		-0.005***	-0.008***	0.004***	0.000
		(-5.446)	(-7.941)	(2.760)	(0.278)
AVG_FIRMSFOLLOWED		-0.000	-0.000	0.002***	0.001*
		(-0.204)	(-0.242)	(3.009)	(1.934)
AVG_TOTALFORECASTS		-0.000	0.000	-0.000***	-0.000**
		(-0.097)	(0.751)	(-3.304)	(-2.484)
AVG_BSIZE		-0.000	-0.000	0.000	-0.000
		(-0.701)	(-1.476)	(0.667)	(-0.299)
Constant		0.110***	0.115***	0.019	0.059*
		(7.867)	(5.679)	(0.966)	(1.867)
Industry and Year FE		Yes	Yes	Yes	Yes
N		4,577	6,850	6,256	5,171
R^2		0.349	0.239	0.104	0.063

Table 4 presents regression results of estimating Equation (2) in subsamples of the poor information environment, proxied by firm-year observations in the highest tercile of analyst forecast dispersion. Estimated coefficients are presented with t-statistics in parenthesis below. Positive (negative) DACC is defined as *DACC*>=0 (*DACC*<0). Good (bad) news is defined as annual stock return >= 0 (< 0). ***, **, and * indicate significance at the p<0.01, 0.05, 0.10 levels. Significance is one-tailed for associations with predicted signs and two-tailed otherwise.

Table 5: Conservative Analyst Following and Meeting or Beating Analyst Consensus

Panel A: Meeting or Beating Analyst Consensus

$$MBE_{,t} = f(\alpha_0 + \alpha_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \alpha_n Controls_{i,t} + \alpha_j IndustryFE + \alpha_k YearFE + \varepsilon_{i,t}) \quad (3)$$

Variable	Predicted Sign	All Poor Info. Env.	Good News	Bad News
AVG_CONSERV_ANALYST$_{t-1}$	**+**	**0.044***	**0.029**	**0.058***
		(1.531)	**(0.736)**	**(1.375)**
SIZE		0.084***	0.094***	0.048
		(4.025)	(3.131)	(1.569)
ROA		0.653***	0.763***	0.455**
		(6.065)	(5.761)	(2.154)
LEVERAGE		-0.213*	-0.185	-0.135
		(-1.710)	(-1.103)	(-0.739)
LOSS		-0.065	-0.057	-0.131*
		(-1.331)	(-0.861)	(-1.751)
BTM		-0.231***	-0.058	-0.199**
		(-3.843)	(-0.536)	(-2.557)
NOA		-0.090	-0.094	-0.186*
		(-1.443)	(-1.252)	(-1.672)
INSTOWN		0.225***	0.317***	0.086
		(2.725)	(2.829)	(0.697)
BIG4		0.132	0.167	0.074
		(1.417)	(1.301)	(0.536)
NUMANALYSTS		0.004	-0.003	0.016***
		(1.093)	(-0.576)	(3.240)
AVG_TOTALEXPERIENCE		0.000	-0.010	0.021
		(0.030)	(-0.516)	(0.868)
AVG_FIRMEXPERIENCE		-0.025	0.014	-0.067**
		(-1.183)	(0.503)	(-1.977)
AVG_FIRMSFOLLOWED		-0.007	-0.010	-0.008
		(-0.902)	(-0.948)	(-0.647)
AVG_TOTALFORECASTS		0.001	0.002	0.000
		(0.443)	(0.763)	(0.023)
AVG_BSIZE		-0.001	-0.003**	0.000
		(-1.185)	(-1.968)	(0.186)
Constant		-1.190***	-1.043**	-1.488
		(-2.867)	(-2.219)	(-1.087)
Industry and Year FE		Yes	Yes	Yes
N		11,421	6,254	5,167
Pseudo R^2		0.0314	0.0348	0.0417

Panel A of Table 5 presents regression results of estimating Equation (3) with *MBE* as the dependent variable in the poor information environment, proxied by the highest tercile of analyst forecast dispersion. Estimated coefficients are presented with t-statistics in parenthesis below. Good (bad) news is defined as annual stock return >= 0 (< 0). ***, **, and * indicate significance at the p<0.01, 0.05, 0.10 levels. Significance is one-tailed for associations with predicted signs and two-tailed otherwise. See Table 1 for sample selection criteria and Appendix A for variable definitions.

Panel B: Beating Analyst Consensus

$$BEAT_{,t} = f(\alpha_0 + \alpha_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \alpha_n Controls_{i,t} + \alpha_j IndustryFE + \alpha_k YearFE + \varepsilon_{i,t}) \quad (3)$$

Variable	Predicted Sign	All Poor Info. Env.	Good News	Bad News
AVG_CONSERV_ANALYST$_{t-1}$	**+**	**0.044***	**0.024**	**0.062***
		(1.508)	**(0.627)**	**(1.458)**
SIZE		0.083***	0.092***	0.048
		(3.969)	(3.066)	(1.567)
ROA		0.655***	0.764***	0.455**
		(6.076)	(5.766)	(2.153)
LEVERAGE		-0.224*	-0.186	-0.153
		(-1.797)	(-1.111)	(-0.839)
LOSS		-0.060	-0.048	-0.130*
		(-1.233)	(-0.726)	(-1.745)
BTM		-0.234***	-0.057	-0.204***
		(-3.901)	(-0.524)	(-2.615)
NOA		-0.090	-0.093	-0.188*
		(-1.443)	(-1.237)	(-1.696)
INSTOWN		0.230***	0.318***	0.097
		(2.789)	(2.837)	(0.785)
BIG4		0.127	0.161	0.072
		(1.365)	(1.254)	(0.519)
NUMANALYSTS		0.004	-0.002	0.016***
		(1.198)	(-0.461)	(3.253)
AVG_TOTALEXPERIENCE		-0.001	-0.011	0.019
		(-0.084)	(-0.589)	(0.785)
AVG_FIRMEXPERIENCE		-0.024	0.016	-0.067**
		(-1.129)	(0.584)	(-1.990)
AVG_FIRMSFOLLOWED		-0.007	-0.010	-0.008
		(-0.870)	(-0.913)	(-0.637)
AVG_TOTALFORECASTS		0.001	0.002	0.000
		(0.466)	(0.753)	(0.058)
AVG_BSIZE		-0.001	-0.003*	0.000
		(-1.136)	(-1.873)	(0.166)
Constant		-1.181***	-1.030**	-1.483
		(-2.852)	(-2.194)	(-1.085)
Industry and Year FE		Yes	Yes	Yes
N		11,421	6,254	5,167
Pseudo R^2		0.0313	0.0346	0.0418

Panel B of Table 5 presents regression results of estimating Equation (3) with *BEAT* as the dependent variable in the poor information environment, proxied by the highest tercile of analyst forecast dispersion. Estimated coefficients are presented with t-statistics in parenthesis below. Good (bad) news is defined as annual stock return >= 0 (< 0). ***, **, and * indicate significance at the p<0.01, 0.05, 0.10 levels. Significance is one-tailed for associations with predicted signs and two-tailed otherwise. See Table 1 for sample selection criteria and Appendix A for variable definitions.

Table 6: Following Size and Forecast Frequency

Panel A: Discretionary Accruals

$$DACC_{i,t} = \beta_0 + \beta_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \beta_n Controls_{n,i,t} + \beta_j IndustryFE + \beta_k YearFE + \varepsilon_{i,t} \quad (2)$$

Variable	Pred. Sign	Small Analyst Following	Large Analyst Following	Low Forecast Frequency	High Forecast Frequency
AVG_CONSERV_ANALYST$_{t-1}$	–	**-0.003***	**-0.002**	**-0.004***	**-0.002**
		(-1.693)	**(-1.057)**	**(-1.745)**	**(-0.842)**
SIZE		-0.011***	-0.003*	-0.010***	-0.003*
		(-5.819)	(-1.897)	(-5.519)	(-1.675)
ROA		-0.074***	-0.036	-0.068***	-0.070***
		(-4.964)	(-1.575)	(-4.497)	(-3.196)
LEVERAGE		0.011	0.049***	0.029***	0.021**
		(1.072)	(4.681)	(2.704)	(2.103)
LOSS		-0.003	0.003	-0.002	0.001
		(-0.718)	(0.908)	(-0.475)	(0.294)
BTM		-0.000	0.022***	-0.001	0.021***
		(-0.081)	(5.096)	(-0.203)	(5.448)
NOA		0.008	0.003	-0.003	0.018**
		(1.071)	(0.383)	(-0.389)	(2.397)
INSTOWN		0.006	-0.001	-0.002	-0.003
		(0.872)	(-0.121)	(-0.294)	(-0.468)
BIG4		-0.003	-0.014	-0.011	0.001
		(-0.372)	(-1.476)	(-1.258)	(0.193)
NUMANALYSTS		-0.001	-0.001**	-0.001***	-0.000
		(-1.200)	(-2.388)	(-2.700)	(-0.072)
AVG_TOTALEXPERIENCE		0.001	-0.003**	0.000	0.000
		(1.088)	(-2.168)	(0.307)	(0.414)
AVG_FIRMEXPERIENCE		-0.000	0.008***	0.002	0.003**
		(-0.337)	(4.492)	(1.425)	(1.962)
AVG_FIRMSFOLLOWED		0.001**	0.002***	0.003***	0.001***
		(2.355)	(2.902)	(3.490)	(2.794)
AVG_TOTALFORECASTS		-0.000***	-0.000***	-0.001**	-0.000***
		(-3.142)	(-2.999)	(-2.432)	(-3.241)
AVG_BSIZE		0.000	0.000	0.000	0.000
		(0.969)	(1.617)	(0.852)	(0.340)
Constant		0.049***	-0.024	0.051**	-0.055*
		(2.638)	(-1.099)	(2.501)	(-1.855)
Industry and Year FE		Yes	Yes	Yes	Yes
N		5,507	5,920	5,712	5,715
R^2		0.067	0.114	0.087	0.088

Panel A of Table 6 presents regression results of estimating Equation (2) in the poor information environment, proxied by the highest tercile of analyst forecast dispersion. Estimated coefficients are presented with t-statistics in parenthesis below. Small (large) analyst following is based on a median split of *NUMANALYSTS*. See Table 1 for sample selection criteria and Appendix A for variable definitions. ***, **, and * indicate significance at the p<0.01, 0.05, 0.10 levels. Significance is one-tailed for associations with predicted signs and two-tailed otherwise.

Panel B: Meeting or Beating Analyst Consensus

$$MBE_{,t} = f(\alpha_0 + \alpha_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \alpha_n Controls_{i,t} + \alpha_j IndustryFE + \alpha_k YearFE + \varepsilon_{i,t}) \quad (3)$$

Variable	Pred. Sign	Small Analyst Following	Large Analyst Following	Low Forecast Frequency	High Forecast Frequency
AVG_CONSERV_ANALYST$_{t-1}$	**+**	**0.021**	**0.104***	**0.022**	**0.097***
		(0.628)	**(1.746)**	**(0.662)**	**(1.630)**
SIZE		0.140***	0.023	0.139***	0.021
		(4.823)	(0.767)	(4.803)	(0.701)
ROA		0.567***	0.781***	0.572***	0.778***
		(4.308)	(3.923)	(4.340)	(3.909)
LEVERAGE		-0.271	-0.217	-0.288*	-0.219
		(-1.598)	(-1.145)	(-1.702)	(-1.155)
LOSS		-0.143**	0.028	-0.134**	0.029
		(-2.147)	(0.375)	(-2.017)	(0.379)
BTM		-0.189**	-0.295***	-0.194**	-0.297***
		(-2.350)	(-3.159)	(-2.418)	(-3.177)
NOA		-0.114	-0.069	-0.114	-0.069
		(-1.450)	(-0.696)	(-1.443)	(-0.697)
INSTOWN		0.234**	0.154	0.233**	0.164
		(2.000)	(1.272)	(2.000)	(1.360)
BIG4		0.149	0.067	0.138	0.069
		(1.303)	(0.402)	(1.210)	(0.413)
NUMANALYSTS		0.010	0.005	0.011	0.005
		(0.770)	(1.008)	(0.862)	(1.039)
AVG_TOTALEXPERIENCE		-0.014	0.038	-0.016	0.038
		(-0.809)	(1.329)	(-0.894)	(1.309)
AVG_FIRMEXPERIENCE		-0.080***	0.037	-0.079***	0.039
		(-2.963)	(1.031)	(-2.945)	(1.069)
AVG_FIRMSFOLLOWED		-0.005	-0.013	-0.004	-0.013
		(-0.416)	(-1.022)	(-0.406)	(-1.005)
AVG_TOTALFORECASTS		0.001	0.001	0.001	0.001
		(0.522)	(0.280)	(0.547)	(0.292)
AVG_BSIZE		-0.002	-0.003	-0.002	-0.003
		(-1.380)	(-1.132)	(-1.315)	(-1.207)
Constant		-0.938*	-1.810***	-0.927*	-1.790***
		(-1.778)	(-3.592)	(-1.765)	(-3.551)
Industry and Year FE		Yes	Yes	Yes	Yes
N		5,502	5,919	5,502	5,919
Pseudo R^2		0.0377	0.0326	0.0376	0.0324

Panel B of Table 6 presents regression results of estimating Equation (3) with *MBE* as the dependent variable in the poor information environment, proxied by the highest tercile of analyst forecast dispersion. Estimated coefficients are presented with t-statistics in parenthesis below. Small (large) analyst following is based on a median split of *NUMANALYSTS*. See Table 1 for sample selection criteria and Appendix A for variable definitions. ***, **, and * indicate significance at the p<0.01, 0.05, 0.10 levels. Significance is one-tailed for associations with predicted signs and two-tailed otherwise.

Panel C: Beating Analyst Consensus

$$BEAT_{,t} = f(\alpha_0 + \alpha_1 AVG\_CONSERV\_ANALYST_{i,t-1} + \alpha_n Controls_{i,t} + \alpha_j IndustryFE + \alpha_k YearFE + \varepsilon_{i,t}) \quad (3)$$

Variable	Pred. Sign	Small Analyst Following	Large Analyst Following	Low Forecast Frequency	High Forecast Frequency
AVG_CONSERV_ANALYST$_{t-1}$	**+**	**0.034**	**0.062***	**0.031**	**0.063***
		(0.884)	**(1.329)**	**(0.815)**	**(1.359)**
SIZE		0.097***	0.068**	0.094***	0.068**
		(3.343)	(2.162)	(3.257)	(2.165)
ROA		0.598***	0.849***	0.603***	0.845***
		(4.610)	(3.991)	(4.653)	(3.972)
LEVERAGE		-0.461***	0.104	-0.487***	0.109
		(-2.656)	(0.586)	(-2.806)	(0.617)
LOSS		-0.017	-0.113	-0.010	-0.111
		(-0.246)	(-1.581)	(-0.154)	(-1.553)
BTM		-0.298***	-0.160*	-0.307***	-0.158*
		(-3.348)	(-1.887)	(-3.456)	(-1.866)
NOA		-0.017	-0.223**	-0.015	-0.225**
		(-0.213)	(-2.054)	(-0.192)	(-2.071)
INSTOWN		0.240**	0.236**	0.243**	0.244**
		(2.080)	(1.977)	(2.108)	(2.042)
BIG4		-0.053	0.325**	-0.061	0.323**
		(-0.436)	(2.275)	(-0.496)	(2.257)
NUMANALYSTS		0.006	0.002	0.007	0.002
		(1.224)	(0.415)	(1.321)	(0.460)
AVG_TOTALEXPERIENCE		0.009	-0.012	0.005	-0.012
		(0.451)	(-0.570)	(0.243)	(-0.538)
AVG_FIRMEXPERIENCE		-0.073**	0.008	-0.070**	0.006
		(-2.312)	(0.271)	(-2.199)	(0.215)
AVG_FIRMSFOLLOWED		-0.041**	0.002	-0.042**	0.002
		(-2.390)	(0.197)	(-2.444)	(0.184)
AVG_TOTALFORECASTS		0.012**	-0.001	0.012**	-0.001
		(2.226)	(-0.635)	(2.364)	(-0.646)
AVG_BSIZE		-0.000	-0.003*	0.000	-0.003*
		(-0.079)	(-1.908)	(0.027)	(-1.938)
Constant		-1.180**	-0.711	-1.160**	-0.709
		(-2.053)	(-1.217)	(-2.015)	(-1.214)
Industry and Year FE		Yes	Yes	Yes	Yes
N		5,703	5,715	5,703	5,715
Pseudo R^2		0.0346	0.0425	0.0347	0.0423

Panel C of Table 6 presents regression results of estimating Equation (3) with *BEAT* as the dependent variable in the poor information environment, proxied by the highest tercile of analyst forecast dispersion. Estimated coefficients are presented with t-statistics in parenthesis below. Small (large) analyst following is based on a median split of *NUMANALYSTS*. See Table 1 for sample selection criteria and Appendix A for variable definitions. ***, **, and * indicate significance at the p<0.01, 0.05, 0.10 levels. Significance is one-tailed for associations with predicted signs and two-tailed otherwise.

Appendix A: Variable Definitions

Independent Variable

AVG_CONSERV_ANALYST$_{t-1}$ = Average conservatism quintile rank in year t-1 of all analysts following the firm in year t. The conservatism of each individual analyst is calculated for each calendar year as $(\beta_0 + \beta_1)/\beta_0$ from the following regression (Hugon and Muslu, 2010):

$$REV_{i,j,t} = \alpha_0 + \alpha_1 BADNEWS_{N,j,t} + \beta_0 \, REV_{N,j,t}$$
$$+ \beta_1 \, BADNEWS_{N,j,t} \times REV_{N,j,t} + \varepsilon_{i,j,t}$$

where:

$REV_{i,j,t}$ = analyst *i*'s earnings forecast revision, calculated as analyst *i*'s forecast of year *t* earnings for firm *j* minus the mean consensus forecast for firm *j*, scaled by the preceding monthly stock price. The mean consensus forecast is based on all forecasts issued in the 30 days prior to the forecast of the nearest neighbor analyst prior to analyst *i*.

$REV_{N,j,t}$ = average revision of analyst *i*'s closest two neighbors (one preceding and the other succeeding analyst *i*), where each revision is calculated as the neighboring analyst's forecast for firm *j* minus the mean consensus forecast for firm *j*, scaled by the preceding monthly stock price;

$BADNEWS_{N,j,t}$ = a bad news indicator, equal to 1 when $REV_{N,j,t,} < 0$ and equal to 0 when $REV_{N,j,t} \geq 0$.

Dependent Variables

DACC	= Discretionary accruals following Kothari et al. (2005). Equal to the residual from estimating the following regression for each industry-year (2-digit SIC code) with at least 10 observations:

$$TACC_t = \beta_0 + \beta_1 (1/AT_{t-1}) + \beta_2(\Delta REV_t - \Delta AR_t) + \beta_3 PPE_t + \beta_4 NI_t + \varepsilon_{i,t}$$

where:

$TACC_t$ = Total accruals (IBC – (OANCF-XIDOC))

AT_{t-1} = Assets (AT) at the beginning of year t

ΔREV_t = Change in total revenue (SALE) from year t-1 to t

ΔAR_t = Change in accounts receivable (RECT) from year t-1 to t

PPE_t = Gross PP&E (PPEGT) in year t

NI_t = Income before extraordinary items (IB) in year t

$TACC_t$, ΔREV_t, ΔAR_t, PPE_t, and NI_t are all scaled by AT_{t-1}

MBE	= 1 (0 otherwise) if actual EPS (from IBES) is greater than or equal to the consensus forecast on the earnings announcement date.
BEAT	= 1 (0 otherwise) if the actual EPS (from IBES) is greater than the consensus forecast on the earnings announcement date.

Control Variables

SIZE	= Natural log of total assets (AT)
ROA	= Return on assets, calculated as income before extraordinary items (IB), scaled by total assets (AT)
LEVERAGE	= Leverage, calculated as total debt divided by total assets [(DLC + DLTT)/AT]
LOSS	= 1 (0 otherwise) if income before extraordinary items (IB) is negative in year t, t-1 or t-2.
BTM	= Book-to-market ratio, calculated as book value of equity divided by market value of equity [CEQ/(CSHO × PRCC_F)]
NOA	= Net operating assets, calculated as operating assets minus operating liabilities, scaled by total assets (AT), where: Operating assets = AT – CHE Operating liabilities = AT – DLC – DLTT – MIBT – PSTK - CEQ
INSTOWN	= Percentage of outstanding shares held by institutions (from Thomson 13-F filings)
BIG4	= 1 (0 otherwise) if the firm is audited by a Big N auditor in year t
NUMANALYSTS	= Number of analysts following the firm in year t
AVG_TOTALEXPERIENCE	= Average number of years that analysts following firm i in year t have issued forecasts in IBES (for any firm)
AVG_FIRMEXPERIENCE	= Average number of years that analysts following firm i in year t have issued forecasts in IBES for firm i.
AVG_FIRMSFOLLOWED	= Average number of firms followed by analysts following firm i in year t.
AVG_TOTALFORECASTS	= Average number of total forecasts issued in year t (for any firm) by analysts following firm i.
AVG_BSIZE	= Average brokerage size (number of analysts) of analysts following firm i in year t.