

FIRM CREDIT RATINGS AND FINANCIAL ANALYST FORECAST PERFORMANCE

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ABSTRACT: *This study examines the relationship between firms' credit ratings and financial analyst earnings forecast performance. We hypothesize and find that high firm credit ratings, which represent low task complexity and low solvency risk, are associated with less dispersion and more accurate earnings forecasts, while low credit ratings are associated with more dispersion and less forecast accuracy. We also find that the quality of firms' earnings reports moderates this relationship. The results of this study are useful to market participants by revealing the increased (decreased) value of information contained in financial analysts' forecasts when firms have received high (low) credit ratings.*

Keywords: *credit ratings, earnings forecasts, forecast accuracy, earnings quality, financial analysts*

JEL: G17; G24

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1. INTRODUCTION

Extant literature finds that high credit ratings are valued by market participants (Hand, Holthausen, & Leftwich, 1992) and are developed with both financial and non-financial information. For example, credit ratings are a function of several factors including, but not limited to, firm solvency (Pottier & Sommer, 1999), quality of earnings reports (Gray, Mirkovic, & Ragunathan, 2006), availability of useful information (Bae et al., 2013), and the number of financial analysts that are following the firm (Cheng & Subramanyam 2008). This paper investigates the information content of credit ratings on financial analyst earnings forecast performance. Such an association has not been investigated in prior literature. We posit that firm credit ratings influence financial analyst forecast accuracy and financial analyst forecast dispersion.

It is reasonable to expect that credit ratings have an association with financial analyst performance in predicting future earnings. First, credit ratings are the result of a comprehensive analysis of a firm's solvency and financial strength. Due to their exemption from Regulation Fair Disclosure (Reg FD), which requires firms to make material information available to all investors at the same time in order to dissuade firms

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from making selective disclosures to certain stakeholders, credit rating agencies have had superior access to management (compared to the information given to financial analysts), and since the inception of Reg FD, the value of credit ratings has increased (Jorion, Zhu, & Charles, 2005).⁴ Because credit ratings contain information about the firm's financial position that financial analysts by regulation are prevented from obtaining, it is reasonable to expect that credit rating information could improve financial analyst performance. Second, because market participants place value on firms with high credit ratings, it is likely that those firms would enjoy easier access to investment dollars and thus have more favorable opportunities for future performance. Additionally, market participants likely expect that a firm with a high credit rating is profitable, solvent, and expected to generate sufficient cash flows to meet future obligations. Furthermore, because high credit ratings are expected to be issued for solvent firms with high quality, transparent disclosures that reduce user uncertainty and complexity, credit ratings represent an assessment of the forecasting environment (Bae et al., 2013). Therefore, credit ratings are expected to denote the level of forecasting difficulty. While high ratings signify less task complexity, low credit ratings would likely be issued for firms with less transparent, lower quality earnings reports, all of which add to uncertainty for financial analysts. Therefore, we hypothesize that credit ratings have a significant impact on the accuracy and dispersion of financial analyst earnings forecasts.

A limited number of studies explore the link between credit ratings and analyst forecasts. However, unlike the present study, these studies do not use the level of credit ratings as an explanatory variable for analyst forecast performance, but instead examine determinants of credit rating levels and changes in ratings following earnings events. For example, research finds that greater analyst following is associated with lower default risk as proxied by credit ratings (Cheng & Subramanyam, 2008). Ederington and Goh (1998) show that following a credit rating downgrade, financial analysts earnings forecasts are also revised downward. However, they do not find that analysts revise their forecasts upward following a credit upgrade. Mansi, Maxwell, and Miller (2011) explore the link between certain analyst characteristics including forecast accuracy and forecast dispersion with credit ratings. Using consensus analyst forecast data, they find that higher forecast dispersion is related to lower credit ratings, but do not find a link between consensus forecast data and credit ratings.

This study is motivated by the intent to better understand the effect that credit rating agencies ultimately have on financial analyst forecasting performance. This examination contributes to the literature by finding an association between earnings forecast performance and credit ratings using individual analyst forecast data and by incorporating the influence of earnings quality and its interactive effect on this association. Because these associations are largely unexamined in prior literature, the results of this study make important contributions to the literature for market participants, particularly by revealing a key determinant of forecast accuracy and dispersion. Specifically, our analysis shows that high credit ratings are associated with more accurate and less dispersed earnings forecasts, and that the quality of the firms' earnings reports moderates this association.

4 Regulation Fair Disclosure took effect on October 23, 2000.

In additional tests, our results hold for alternate specifications of forecast accuracy. These results provide an important and unique contribution to the financial analyst forecast performance literature and add new knowledge to the literature in several important ways. First, by informing analysts of the predictive value contained in credit ratings these results support analysts' efforts to produce accurate earnings predictions. Second, by informing market participants how credit ratings are processed by financial analysts, investors will benefit from the knowledge that future earnings forecasts are likely more accurate for a firm with higher credit ratings. Third, these results provide regulators with substantiation of the value of high quality earnings reports. Finally, the results of this study aid future researchers by revealing the significant influence that credit ratings have on financial analyst forecasting performance.

The remainder of this paper is arranged as follows: section 2 provides a review of the related literature, section 3 describes the research method used, section 4 presents the test results, section 5 offers the results of additional analysis and sensitivity testing, and section 6 provides a summary and conclusion.

2. LITERATURE REVIEW

Extant literature finds that high credit ratings are prized by market participants (Hand, Holthausen, & Leftwich, 1992), and that the market reacts negatively to poor credit ratings (Norden & Weber, 2004). Some argue that the information in bond ratings provide little incremental data and has little value to the equity markets (Partnoy, 1999), however following the announcement of credit ratings, there is a reaction in bond prices (Kliger & Sarig, 2000; Norden & Weber, 2004). One explanation for this reaction is that a firm's credit rating conveys inside information about the company to the market, favorable or unfavorable, without disclosing details to the public (Kliger & Sarig, 2000). Alternately, some argue that credit rating agencies do not take advantage of this additional access to insider information (Frost, 2007). Since the inception of Reg FD, which provided an exception to credit rating agencies in providing information that is not publicly available, the value of credit ratings has increased (Jorion, Zhu, & Charles, 2005). Finally, research shows that credit ratings produced using information from various public and private sources (Gray, Mirkovic, & Rangunathan, 2006), are influenced by several factors including firm solvency (Pottier & Sommer, 1999), earnings quality (Gray, Mirkovic, & Rangunathan, 2006), availability of useful information (Bae et al., 2013), and financial analyst following (Cheng & Subramanyam, 2008). This paper adds to the literature by demonstrating the contribution that credit ratings make to the environment in which financial analyst earnings forecasts are generated.

The literature on financial analyst earnings forecast can be classified as analyst level, firm level, or the market level. Taken together, factors in each of these classifications affect how analysts arrive at their estimates. There are unique characteristics that affect the accuracy of each individual financial analyst. For example, the experience that a financial analyst has forecasting for a specific firm has been found to be associated with forecast accuracy (Clement, 1999; Jacob, Lys, & Neale, 1999; Mikhail, Walther, & Willis, 1997). The size and

type of firm where a financial analyst is employed is associated with accuracy (Clement, 1999; Jacob, Rock, & Weber, 2008). Additionally, an increase in the number of firms and the complexity of the portfolio of firms followed by a financial analyst leads to a decrease in the accuracy of financial analysts (Clement, 1999). Finally, the information emphasized by financial analysts differs with the individual financial analyst's prior level of accuracy (McEwen & Hunton, 1999). Other literature analyzes the effect of the market environment on the accuracy of financial analyst forecasts. The firm's local GAAP is also shown to have an effect on forecast estimates (Bae, Tan, & Welker, 2008; Basu, LeeSeok, & Ching-Lih, 1998; Glaum et al., 2013). Specifically, accounting standards that are based on net asset value lead to more accurate forecasts than standards based on historical cost reporting (Liang & Riedl, 2014). Certain market regulations also have an effect on financial analysts accuracy (Guan, Lu, & Wong, 2012). At the firm level, there are also important determinants of financial analyst forecast accuracy. The clarity, quality and extent of disclosures have an effect on financial analyst (Byard & Shaw, 2003; Dhaliwal et al., 2012). The extent to which a firm has diversified its holdings and operations internationally also has a measured effect on how accurately financial analysts can forecast earnings for that firm (Duru & Reeb, 2002; Mauri, Lin & Neiva DeFigueiredo, 2013). This study contributes to the accuracy literature by identifying another firm level determinant of forecast accuracy. Our results provide further understanding of the source of forecast accuracy by revealing the role that firm credit ratings play in forecast accuracy.

The information content of earnings and the quality of earnings have been extensively examined in the literature (e.g. Dechow & Dichev, 2002; Francis et al., 2004). Several methods of measuring the quality of earnings have been employed to document a firm's use of accruals in their reported earnings (e.g. Cohen, Dey, & Lys, 2008). Dechow and Dichev (2002) utilize a model that measures whether current accruals are associated with prior, current, or next period cash flows. Their model assumes that accruals should map to cash flows in a timely manner. The mapping of accruals to cash flows is a widely utilized method to measure the quality of cash flows and to determine if managers are manipulating earnings (e.g. Francis et al., 2005).

Investors and managers alike widely believe that firms manage earnings to some degree (Graham, Harvey, & Rajgopal, 2005). Dechow and Skinner (2000) classify firms into one of several groups according to the extent to which they engage in earnings management including a conservative accounting group, a neutral earnings group, an aggressive accounting group, or a fraudulent accounting group. One form of earnings management is the manipulation of earnings to develop a smooth earnings path (Murphy 2001). Some extant research finds that smooth earnings are desirable. For example, Barth, Elliott, and Finn (1999) argue that investors prefer and reward a smooth earnings path. Conversely, Leuz, Nanda, and Wysocki (2003), contend that management manipulates earnings to conceal true firm performance from outsiders, thus decreasing the level of investor protection. Still, no clear link has been shown between earnings smoothness and firm valuation (Gao & Zhang 2015). We add to the earnings management and earnings smoothing literature by demonstrating the role that the quality of earnings plays in the link between credit ratings and the accuracy of forecasted earnings.

A limited number of studies explore the link between credit ratings and analyst forecasts. A larger number of analysts following a firm is associated with lower default risk as proxied by credit ratings (Cheng & Subramanyam, 2008). Ederington and Goh (1998) show that following a credit rating downgrade, financial analysts earnings forecasts are also revised downward. However, they do not find that analysts revise their forecasts upward following a credit upgrade. Mansi, Maxwell, and Miller (2011) do explore the link between certain analyst characteristics including forecast accuracy and forecast dispersion. Using consensus analyst forecast data, they find that higher forecast dispersion is related to lower credit ratings, but do not find a link between consensus forecast data and credit ratings. This paper contributes to the literature by finding an association between earnings forecasts and credit ratings using individual analyst forecast data and by incorporating the influence of earnings quality and its interactive effect on this association.

3. RESEARCH METHOD

As described above, credit ratings are a function of a firm's solvency, quality of its earnings reports, financial strength, and the availability of other useful information by which to predict the firm's future earnings and cash flows. Thus, we expect that the information contained in credit ratings, regarding any one or all of these factors, add additional information into the forecasting environment that financial analysts have available to them in generating their forecasts.

We start our analysis by first considering the effect of the existence of a credit rating (irrespective of good or bad) on financial analyst forecast accuracy and dispersion. In the latter part of 2000, Reg FD was put into effect by the Security and Exchange Commission. Prior to Reg FD, firms could selectively choose which financial information they supplied to financial analysts. The concern was that "firm-friendly" financial analysts were given better access than other financial analysts, and they in turn would be inclined to issue more optimistic earnings forecasts. Prior to Reg FD, if financial analysts issued unfavorable forecasts or recommendations, it might have resulted in their losing this preferred access to management (Barniv et al., 2009). Although Reg FD precluded such selective disclosures to financial analysts, credit rating agencies were specifically exempt from the regulation. As a result, credit rating agencies continue to have access to more timely information and to information that may not have been disclosed to financial analysts. Therefore, credit ratings may contain additional information than that which is disclosed or made available to financial analysts. It follows, then, that the existence of a credit rating adds another potential piece of information for a financial analyst to consider in developing their forecast, which would be lacking for a firm without a credit rating. Consequently, the mere existence of a credit rating may, in and of itself, have an incremental effect on analyst forecast performance.

It may seem obvious that the existence of a credit rating offers additional information for a financial analyst to consider in developing their earnings forecast and, therefore, would result in greater forecast accuracy. Indeed, there is a reasonable presumption that any

information in addition to whatever might already be on hand or publicly available would be helpful. However, when an analyst is facing a forecasting environment with less available information (i.e. the lack of a credit rating), they may become more diligent in their analysis of the information that is available to them, resulting in greater accuracy (Lehavy, Li, & Merkley, 2011; Lobo, Song, & Stanford, 2012). Thus, a reasonable inquiry could be framed concerning this dichotomy. Does the existence of a credit rating lull analysts into a false sense of security, perhaps even encouraging some laziness in their analysis of the robustness of a firm's earnings, or does the credit rating offer some helpful, pertinent information to analysts in the performance of their forecasts? Given that the mere existence of a credit rating may have differential effects on financial analysts, we do not predict a positive or negative effect of the existence of a credit rating on forecast accuracy or dispersion. To investigate this assertion, we test the following hypothesis, stated in the null form.

HYPOTHESIS 1. The existence of a credit rating has no effect on financial analyst earnings forecast accuracy or financial analyst forecast dispersion.

Next, we turn our attention towards financial analyst forecast performance in only cases where a credit rating does exist. Specifically, we consider the effect of the level or quality of the credit rating on analyst forecast performance.

As noted in the discussion above, due to their exemption from Reg FD, credit rating agencies have better and timelier access to information than financial analysts. Credit ratings, however, can convey either positive or negative signals about a firm. Firms with high credit ratings are firms with high liquidity, favorable cash flows, and strong overall financial health. Conversely, firms with low credit ratings are firms with low liquidity, weak cash flows, and are in financial distress. These two scenarios offer very different information to a financial analyst about a firm.

For firms with high credit ratings, the forecasting environment is likely robust with high quality information about a high quality firm and the task complexity involved in generating a forecast is likely relatively low. Firms with high credit ratings are also more likely to have more consistent earnings patterns (Gray, Mirkovic, & Raganathan, 2006). With more consistent earnings patterns, financial analysts are more likely to make more accurate forecasts for these firms. In other words, high credit ratings act as both favorable new incremental information about a firm and as additional confirmation of the quality of the other information already available to analysts.

For firms with low credit ratings, the forecasting environment is likely lacking quality information about a firm and the task complexity involved in generating a forecast is likely relatively high. Additionally, it is reasonable to expect that firms with low credit ratings experience more frequent losses (Ashbaugh-Skaife, Collins, & LaFond, 2006). Firms with losses and more volatile earnings patterns complicate the task for financial analysts (Elliott & Hanna, 1996). As a result, low credit ratings may offer very little new incremental information about a firm and may actually introduce more noise into the forecasting environment.

Furthermore, the literature indicates that user uncertainty may reduce financial analyst performance and that such uncertainty about a firm's economics increases dispersion patterns of financial analyst forecasts (Barron & Stuerke, 1998; Imhoff & Lobo, 1992; Payne & Robb, 2000). Prior studies also indicate that high quality, transparent disclosures reduce user uncertainty and task complexity (Lang & Lundholm, 1996), and that credit rating agencies issue higher ratings for firms with such disclosures (Bae et al., 2013). Credit ratings, therefore, represent an assessment of the forecasting environment. Low credit ratings are usually associated with high levels of long term risk, signaling possible future defaults, and noisier information environments (Pottier & Sommer, 1999). Therefore, credit ratings denote the level of forecasting difficulty. Thus, high ratings signify less task complexity and are expected to result in increased forecast performance, while low credit ratings are likely issued for firms with less transparent, lower quality earnings reports, which add to uncertainty for financial analysts and are expected to reduce forecast performance. Because credit ratings represent a high level assessment of a firm's long term risk and credit-worthiness, and contain information not available to financial analysts in a timely manner, it is reasonable to expect that financial analyst forecast accuracy will be improved by the information contained in credit ratings. To investigate this assertion we test the following hypotheses, stated in the alternate form.

HYPOTHESIS 2. Financial analyst earnings forecast accuracy is increased and financial analyst forecast dispersion is decreased for firms with high credit ratings.

The literature on how the quality of earnings could either increase or decrease forecasting performance is unclear. For example, low quality earnings reports could decrease forecast performance by creating a more complex, misleading information environment resulting in over (or under) estimates. Literature finds that low quality reports could be expected to result in more uncertainty about a firm's future, and uncertainty is found to 1) increase dispersion patterns of financial analyst forecasts (Barron & Stuerke, 1998; Imhoff & Lobo, 1992; Payne & Robb, 2000) and, 2) reduce cash flow forecast accuracy (Bilinski, 2014). Thus, low earnings quality could result in misleading, and therefore unreliable earnings reports. A weak link between earnings and cash flows will increase information risk (Francis et al., 2005) and low earnings quality could weaken that link. Barton, Hansen, and Pownall (2010) find that reported earnings are more value relevant when that link is strong.

Alternatively, low earnings quality could indicate the potential for more accuracy and less dispersion in financial analysts' forecasts. First, a misleading and complex forecasting environment could encourage financial analysts to resort to herding behavior. Herding behavior theory (Hong, Kubik, & Solomon, 2000; Mensah & Yang, 2008) suggests that financial analysts will change their own private opinions about a company's earnings potential with the purpose of issuing earnings forecasts which are closer to the consensus. Therefore, they modify their forecasts to coalesce around the estimate of other possibly more experienced financial analysts, thus increasing their forecasting performance. Furthermore, when earnings management is performed (through the use of discretionary accruals or other methods) with the intent of smoothing reported earnings, a reduction

in the variability of earnings could result (Demerjian, Lewis-Western, & McVay, 2015). Therefore, the reduced earnings quality, due to the use of discretionary accruals to meet earnings benchmarks (such as meeting financial analysts' expectations), can result in the convergence of reported earnings with financial analysts' forecasts (Burgstahler & Eames, 2006; Matsumoto, 2002; Payne & Robb, 2000). Such a convergence reduces the forecast errors used to measure forecast performance.

Second, firms that manage earnings typically have lower earnings quality (Dechow, Ge, & Schrand, 2010). Firms are likely to manage earnings to meet certain benchmarks such as positive earnings, growth in earnings or to meet financial analyst expectations (Graham, Harvey, & Rajgopal, 2005). Therefore, if firms manage earnings to meet financial analyst expectations, thus resulting in greater financial analyst accuracy, they will have lower earnings quality than firms that do not manage earnings.

For both of these reasons, poor earnings quality would be associated with increased financial analyst performance (more accuracy and less dispersion among forecasts). Therefore, because we believe that lower earnings quality is likely to indicate either herding of financial analysts' forecasts or the presence of earnings management, we predict that low earnings quality will have a positive relationship with forecast accuracy and will reduce forecast dispersion.

HYPOTHESIS 3. Financial analyst earnings forecast accuracy is increased and financial analyst forecast dispersion is decreased for firms with low earnings quality.

While we hypothesize that higher credit ratings and lower earnings quality will lead to an increase in financial analyst forecast accuracy and a decrease in financial analyst forecast dispersion, we predict that, when taken together, the effect of higher credit ratings on financial analyst performance will be moderated by the effect of earnings quality. This reduction of analyst performance when both higher credit ratings and lower earnings quality is present may occur for two reasons. First, more profitable firms are more likely to receive higher credit ratings (Ashbaugh-Skaife, Collins, & LaFond, 2006). These more profitable firms that receive higher credit ratings are less likely to be motivated to manipulate their earnings and participate in myopic management.⁵ Since these more profitable firms are not willing to manipulate their earnings to meet analysts' expectations, financial analyst accuracy declines and financial analyst dispersion increases. Second, larger firms are also likely to receive higher credit ratings (Gray, Mirkovic, & Ragunathan, 2006). Larger firms that receive higher credit ratings are less likely to manipulate their earnings since larger and more diversified firms have more consistent earnings and therefore have less motivation to manipulate earnings to meet analyst expectations. Since more profitable firms and larger firms could be less likely to manipulate earnings, we hypothesize that the effect of credit ratings and earnings quality on analyst performance will be moderated as follows:

⁵ Myopic management is the manipulation of earnings to achieve specific targets that leads to a long term reduction in firm performance (see Mizik, 2010).

HYPOTHESIS 4. *Earnings quality has a moderating effect on the influence that credit ratings have on forecast accuracy and dispersion such that as earnings quality diminishes, forecast accuracy declines and forecast dispersion increases.*

3.1. Dependent Variables

To investigate the association between firm credit ratings and financial analyst forecast accuracy, we use the absolute forecast error scaled by share price (equation 1) from prior literature (Bae, Tan, & Welker, 2008; Dhaliwal et al., 2012; Duru & Reeb, 2002; Glaum et al., 2013) as follows:

$$AFEP_{i,j,t} = \frac{|FORECAST_{i,j,t}^{t-1} - NI_{j,t}|}{PRICE_{j,t}} (-100) \quad (1)$$

where for analyst i , firm j , and at time t :

$FORECAST$	= forecasted net income
NI	= reported net income
$PRICE$	= stock price.

For ease of interpretation the result is then multiplied by -100 such that an increase in $AFEP$ indicates an increase in forecast accuracy. Therefore, higher values of $AFEP$ indicate higher or more accurate levels of forecasted earnings.

Following prior literature, we measure forecast dispersion ($DISP$) as the standard deviation of forecasts deflated by stock price (Mansi, Maxwell, & Miller, 2011) as follows:

$$DISP_{j,t} = \frac{\sigma(FORECAST_{i,j,t})}{PRICE_{j,t}} \quad (2)$$

σ	= standard deviation for firm j at time t
$FORECAST$	= forecasted net income
$PRICE$	= stock price

Therefore, higher values of $DISP$ indicate more forecast dispersion among financial analysts. While this dependent variable is not composed of an actual measure of earnings, dispersion can be interpreted as a proxy for differences in opinion among financial analysts for a security (Diether et al., 2002) and, therefore, uncertainty in earnings forecasts. Prior studies also find that wide dispersion patterns in forecast values indicate complexity in making earnings forecasts (Duru & Reeb, 2002; Mauri, Lin, & DeFigueiredo, 2013; Tan, Wang, & Welker, 2011).

3.2. Independent Variables

The credit rating variable (*CR*) is the S&P Domestic Long-term issuer credit rating from Compustat (mnemonic: SPDRM). It is defined as the Standard & Poor's Issuer Credit Rating which represents the "current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations. This opinion focuses on the obligor's capacity and willingness to meet its long-term financial commitments (those with maturities of more than one year) as they come due." *CR* ranges from one to 22, with one representing a D rating and 22 representing a AAA rating. Therefore, higher values of *CR* denote that a firm has received a higher credit rating from S&P.

3.3. Control Variables

We include the controls *FOLLOW*, *LOSS*, $\Delta EARN$, *HORIZ*, and *VOL* from prior literature (Duru & Reeb, 2002; Mauri, Lin, & DeFigueiredo, 2013), all of which except for *FOLLOW* control for complexity and uncertainty in the forecasting task. We also include controls for the quality of reported earnings (*EQ*) and for the smoothness of reported earnings (*SMOOTH*), both of which could also introduce uncertainty into the forecasting environment. Finally, following Duru and Reeb (2002) and Bae, Tan and Welker (2008) we also include controls for industry and fiscal year. *FOLLOW* is measured as the total number of financial analysts following the firm for a given period. The typical expectation is that larger financial analyst following is associated with lower forecast optimism and greater accuracy (Drake & Myers, 2011; Duru & Reeb, 2002; Mauri, Lin, & DeFigueiredo, 2013). Furthermore, Lang and Lundholm (1996) indicate that larger following is associated with decreases in overestimates because financial analysts prefer to follow firms with high quality earnings reports. However, Duru and Reeb (2002) find greater following to be positively and marginally associated with forecast accuracy and not a significant factor for overestimates. In light of the above studies, if significant, we expect *FOLLOW* to be negatively associated with dispersion and positively associated with accuracy. *LOSS* (an indicator variable coded 1 if the firm reported a net loss in the period, otherwise zero) is included because managers of firms that report losses may tend to understate net income in order to enhance net income in subsequent periods; a practice known in the literature as taking a "big bath" (Elliott & Hanna, 1996; Moehrl, 2002). Firms that engage in such practices understate net income which causes forecasts to be higher than reported income. Additionally, Brown (2001) finds that financial analysts issue more optimistic forecasts in periods of losses, and Hwang, Jan, & Basu (1996) find that financial analysts are less accurate while forecasting losses than when predicting positive net income. However, Duru and Reeb (2002) find that *LOSS* is not significant for accuracy. We expect *LOSS* to be positively associated with dispersion and negatively associated with accuracy. The $\Delta EARN$ variable is equal to the absolute value of the change in earnings per share from the previous year divided by the stock price at the beginning of the year. Duru and Reeb (2002) find that larger absolute changes in earnings per share are negatively associated with accuracy. However, because large changes in earnings could present uncertainty, we do not predict a direction. Following prior literature the forecast horizon control

(*HORIZ*) captures the number of calendar days between the forecast issue date and the actual earnings announcement date. The literature shows that longer forecast horizons are associated with less accurate (Brown, 2001; Clement & Tse, 2003; Jacob, Lys, & Neale, 1999) and more biased optimistic forecasts (Duru & Reeb, 2002; Mansi, Maxwell, & Miller, 2011). We expect longer horizons to be associated with more dispersion and less accuracy. Volatile earnings are known to be associated with less accurate earnings forecasts (Duru & Reeb, 2002; Lim, 2001; Kross, Ro, & Schroeder, 1990). Thus, we expect that highly volatile earnings add complexity and uncertainty to the forecasting task. To control for volatility in earnings we include the variable *VOL*, which is equal to the standard deviation of the annual earnings per share values for the firm.

Because low quality earnings could provide misleading information on which to base earnings forecasts, which could complicate the forecasting task, we control for earnings quality (*EQ*) following prior literature and we measure the degree to which reported earnings reflect the actual cash flows of the firm (Dechow & Dichev, 2002; Francis et al., 2004). It measures whether current accruals are associated with prior, current, or next period cash flows. Changes in working capital that do not map to those cash flows are thought to reduce the quality of earnings. Following Dechow and Dichev (2002), the dependent variable is the change in working capital (ΔWC), and equals $\Delta AR + \Delta Inventory - \Delta AP - \Delta TP + \Delta Other$ Assets-net, where *AR* equals accounts receivable, *AP* equals accounts payable, and *TP* equals taxes payable. Following prior literature, all variables are then scaled by the firm's average assets:

$$\Delta WC_{jt} = \alpha + \beta_1 CFO_{j,t-1} + \beta_2 CFO_{jt} + \beta_3 CFO_{j,t+1} + v_{jt} \quad (3)$$

where ΔWC_{jt} is firm *j*'s change in working capital from the prior year (*t-1* to year *t*), CFO_{jt} is firm *j*'s cash flow from operations in year *t*, and v_{jt} is the residuals for firm *j*, year *t*. The residual represents changes in working capital from accruals that do not map to cash flows in a timely manner (*t-1*, *t*, or *t+1*). The standard deviation of a time-series of the absolute values of the residuals is computed for each firm which represents the volatility of earnings quality over a five-year period (*EQ*). For earnings quality to have an impact on financial analyst's performance, the information must be available prior to the forecast date, therefore *EQ* is lagged by one year.

3.4. Econometric Models

To test Hypothesis 1, the test of whether the existence of a credit rating has an effect on the performance of analysts, we estimate the following:

$$\begin{aligned} \text{Dependent} = & \alpha + \beta_1 CREXIST_{ij} + \beta_2 FOLLOW_{ij} + \beta_3 LOSS_{ij} + \beta_4 \Delta EARN_{ij} + \beta_5 HORIZ_{ij} \\ & + \beta_6 VOL_{ij} + \beta_7 IND_{ij} + \beta_8 YEAR_{ij} \end{aligned} \quad (4)$$

where *Dependent* is either *AFEP* (analyst forecast accuracy variable measured as the absolute value of the forecast error scaled by the lag of the firm's market price) or *DISP* (analyst forecast dispersion variable measured as the standard deviation of forecasts deflated by the stock price), *CREXIST* is an indicator variable coded as 1 if the observation includes a Standard & Poor's Credit Rating, and 0 otherwise. *FOLLOW* is the number of financial analysts following the firm's earnings for the period, *LOSS* is an indicator variable coded one if the firm reported a net loss in the period, otherwise zero, $\Delta EARN$ is equal to the absolute value of the change in earnings per share from the previous year divided by the stock price at the beginning of the year, *HORIZ* is the number of calendar days between the forecast issue date for the company and the actual earnings announcement date, *VOL* is the standard deviation of earnings per share for the firm, *IND* represents industry controls for the company based on the I/B/E/S SIG codes, and *YEAR* represents indicator variables for the firm's fiscal year.

To test Hypotheses 2 and 3, we estimate equation (5). Hypothesis 2 anticipates a positive association between earnings forecast accuracy and firm credit ratings as well as a negative association between earnings forecast dispersion and firm credit ratings. Hypothesis 3 anticipates a negative association between earnings quality and forecast accuracy as well as a positive association between earnings quality and earnings forecast dispersion. Equation (5) is estimated as follows:

$$Dependent = \alpha + \beta_1 CR_{ij} + \beta_2 EQ_{ij} + \beta_3 FOLLOW_{ij} + \beta_4 LOSS_{ij} + \beta_5 \Delta EARN_{ij} + \beta_6 HORIZ_{ij} + \beta_7 VOL_{ij} + \beta_8 IND_{ij} + \beta_9 YEAR_{ij} \quad (5)$$

where *CR* is the credit rating variable and ranges from one to 22 (one representing a D rating and with 22 representing a AAA rating), *EQ* represents the lag of the standard deviation of the firm's level of earnings quality over the prior five consecutive years, and all other variables are defined as in equation (4).

Finally, to test Hypotheses 4, which anticipates that at higher levels of credit ratings, the negative association between earnings quality and financial analyst forecast accuracy as well as the positive association between earnings quality and financial analyst forecast dispersion is reduced, we estimate equation (6). We include the interaction of credit ratings with earnings quality (*CR*EQ*) in our basic models as follows:

$$Dependent = \alpha + \beta_1 CR_{ij} + \beta_2 EQ_{ij} + \beta_3 CR*EQ_{ij} + \beta_4 FOLLOW_{ij} + \beta_5 LOSS_{ij} + \beta_6 \Delta EARN_{ij} + \beta_7 HORIZ_{ij} + \beta_8 VOL_{ij} + \beta_9 IND_{ij} + \beta_{10} YEAR_{ij} \quad (6)$$

3.5. Data Sample

We collect a sample of company level reported data, including credit ratings, for the period 2006 to 2015 from the Compustat Annual Database. We combine individual financial analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S) for the

same period. After merging data from these sources, we omit any firm-year observations with insufficient data, any firm-year observations with a financial analyst following of less than two, with a horizon of more than one year, and then limit the sample to the most recent forecast for each financial analyst in each firm year. The resulting full sample contains 100,137 firm year observations. This sample is used in our testing of Hypothesis 1. We then reduce the sample to only observations which contain a Standard and Poor's credit rating for each firm-year. This reduces the sample size to 88,652 observations. This reduced sample is utilized to test the remaining Hypotheses 2 – 4.

Table 1

Descriptive Statistics (n=100,137)					
Variable	Mean	Median	Standard deviation	25th Percentile	75th Percentile
<i>AFEP</i>	-8.9569	-0.1772	1329.4	-0.5613	-0.0573
<i>DISP</i>	0.5133	0.0048	88.730	0.0021	0.0119
<i>CR</i>	8.1187	10.000	7.1398	0.0000	14.000
<i>EQ</i>	0.0333	0.0245	0.0324	0.0160	0.0396
<i>FOLLOW</i>	19.891	19.000	11.156	11.000	27.000
<i>LOSS</i>	0.1649	0.0000	0.3711	0.0000	0.0000
Δ <i>EARN</i>	1.2643	0.0119	223.74	0.0056	0.0277
<i>HORIZ</i>	103.86	97.000	81.971	43.000	116.00
<i>VOL</i>	0.0626	0.0318	0.1485	0.0160	0.0661

AFEP is the absolute forecast error multiplied by -100. *DISP* is forecast dispersion, measure using the standard deviation of analysts' earnings forecasts deflated by the stock price on the forecast date. *CR* is the Standard & Poor's Issue Credit Rating which is the opinion of an issuer's overall creditworthiness with codes ranging from 1 representing a D rating and 22 representing a AAA rating lagged by one period. *EQ* is the earnings quality of the firm calculated as the lag of the standard deviation of the residuals from firm-specific regressions of changes in working capital on past, present, and future operating cash flows over the prior five consecutive years. *FOLLOW* is the number of analysts following the firm per I/B/E/S. *LOSS* is an indicator variable coded as 1 for firm-year observations with negative earnings, and 0 otherwise. Δ *EARN* is the change in earnings, measured as the absolute value of the difference between the current year's earnings per share and the previous year's earnings per share. *HORIZ* is the forecast horizon, expressed as the number of days between the forecast and the end of the fiscal year. *VOL* is earnings volatility, measure as the standard deviation of earnings per share for the previous 5-year period.

Table 1 provides the descriptive statistics for the test variables of our models. The mean and median values of -8.9569 and -0.1772 for *AFEP* are negative by design and indicate the difference between a financial analyst's earnings forecast and the actual earnings. The median value for *CR* is 10, the equivalent of a BB- rating which Standard and Poor's defines as indicative that the obligor faces major ongoing uncertainties. The average forecast horizon for the sample is only 103.86 days or more than three months. The mean and median values for *FOLLOW* are 19.891 and 19 and the 25th and 75th percentiles are 11 and 27 indicating that the majority of the firms in the sample have more than a dozen financial analysts providing estimates for the firms for any given firm-year. The variable

EQ has mean and median values of 0.0333 and 0.0245 as measured using the lag of changes in working capital on past, present and future operating cash flows over the prior five consecutive years. While the period for our sample covers the years from 2006 to 2015, this variable draws on data that extends back to the year 2001 due to its use of information from prior periods to construct firm-specific regressions regarding the mapping of cash flows to accruals. The mean value for *LOSS* is 0.1649 indicating that only a small portion of the sample includes firms with negative annual earnings.

Table 2

Pearson/Spearman Correlations (n=100,137)									
	<i>AFEP</i>	<i>DISP</i>	<i>CR</i>	<i>EQ</i>	<i>FOLLOW</i>	<i>LOSS</i>	Δ <i>EARN</i>	<i>HORIZ</i>	<i>VOL</i>
<i>AFEP</i>	1	-0.62357 <.0001	0.11709 <.0001	-0.07246 <.0001	0.14784 <.0001	-0.32649 <.0001	-0.43561 <.0001	-0.15724 <.0001	-0.24791 <.0001
<i>DISP</i>	-0.63008 <.0001	1	-0.15145 <.0001	0.09655 <.0001	-0.16367 <.0001	0.45636 <.0001	0.54070 <.0001	-0.01567 <.0001	0.37320 <.0001
<i>CR</i>	0.19711 <.0001	-0.24303 <.0001	1	-0.16883 <.0001	0.36279 <.0001	-0.19109 <.0001	-0.14302 <.0001	-0.09893 <.0001	-0.25994 <.0001
<i>EQ</i>	-0.12222 <.0001	0.15802 <.0001	-0.20313 <.0001	1	-0.15136 <.0001	0.07581 <.0001	0.12569 <.0001	0.02829 <.0001	0.22144 <.0001
<i>FOLLOW</i>	0.24023 <.0001	-0.23126 <.0001	0.41250 <.0001	-0.19041 <.0001	1	-0.13684 <.0001	-0.17202 <.0001	-0.08250 <.0001	-0.12465 <.0001
<i>LOSS</i>	-0.31926 <.0001	0.44566 <.0001	-0.21774 <.0001	0.07663 <.0001	-0.14276 <.0001	1	0.31492 <.0001	0.03120 <.0001	0.38453 <.0001
Δ <i>EARN</i>	-0.39958 <.0001	0.59119 <.0001	-0.18572 <.0001	0.16353 <.0001	-0.18002 <.0001	0.29278 <.0001	1	0.00675 0.0326	0.35388 <.0001
<i>HORIZ</i>	-0.16101 <.0001	-0.02395 <.0001	-0.15771 <.0001	0.04341 <.0001	-0.14183 <.0001	0.04475 <.0001	0.00025 0.9376	1	0.02866 <.0001
<i>VOL</i>	-0.34879 <.0001	0.53286 <.0001	-0.29018 <.0001	0.27947 <.0001	-0.11008 <.0001	0.41424 <.0001	0.43373 <.0001	0.00237 0.4539	1

Pearson correlations are shown above the diagonal. Spearman are shown below. Note that the correlation value is shown with the associated p-value immediately below. All variables are defined in Table 1.

Table 2 provides the Pearson and Spearman correlations. The Pearson correlations are reported above the diagonal and the Spearman correlations are reported below the diagonal. Most of the correlations between the independent variables exhibit relatively small correlations. The test variables, *AFEP* and *CR* are positively correlated for both the Pearson and Spearman measures. Additionally, *DISP* and *CR* are negatively correlated for both the Pearson and Spearman measures. This offers preliminary evidence regarding Hypothesis 2.

4. RESULTS

Panel A of Table 3 shows the results of estimating equation (4) with *AFEP* as the dependent variable, while Panel B provides the results of the same model with *DISP* as the dependent variable. The coefficient on *CREXIST* is negative and significant at the one percent level

for the test with *AFEP* as the dependent variable, indicating that the existence of a credit rating is associated with less financial analyst forecast accuracy. Similarly, for the test with *DISP* as the dependent variable, the coefficient on *CREXIST* is positive and significant. This indicates that the existence of a credit rating is associated with greater dispersion in forecast patterns. As discussed in Section 3, while a credit rating contains information that may improve the forecast performance of financial analysts, the results in Table 3 indicate less accuracy and more dispersion for firms where a credit rating exists. This could be due to the theory that analysts exert more effort in making their forecasts when there is less available information. Therefore, by rejecting Hypothesis 1, which was stated in the null form, we find a significant association between the existence of a credit rating and analyst forecast performance.

Table 3

Rating Availability with AFEP and DISP including EQ		
Independent Variable	Panel A	Panel B
	Dependent variable: <i>AFEP</i>	Dependent variable: <i>DISP</i>
	Coefficient	Coefficient
Intercept	0.3588 ***	0.0000 ***
<i>CREXIST</i>	-0.0674 ***	0.0006 ***
<i>FOLLOW</i> ¹	10.440 ***	-0.0974 ***
<i>LOSS</i>	-1.1006 ***	0.0163 ***
Δ <i>EARN</i>	-14.110 ***	0.1596 ***
<i>HORIZ</i> ¹	-4.1100 ***	0.0015 **
<i>VOL</i>	-1.4896 ***	0.0378 ***
<i>IND</i>	Included	Included
<i>YEAR</i>	Included	Included
Adjusted <i>R</i> ²	0.2752	0.4196
<i>n</i>	100,137	100,137

*, **, *** indicate statistical significance utilizing heteroscedasticity consistent standard errors at the 10%, 5%, and 1% levels, respectively. ¹These coefficients are multiplied by 1,000 for ease of interpretation. *CREXIST* is an indicator variable coded as 1 if the observation includes a Standard & Poor's Issue Credit Rating, and 0 otherwise. *IND* is an industry control using the I/B/E/S industry classification. *YEAR* is an annual control representing the year in which firm *j*'s earnings are reported. All other variables are defined in Table 1.

Consistent with prior literature, *FOLLOW* is significant in both tests indicating that when more financial analysts follow a firm, financial analysts are more accurate and are less dispersed in their earnings forecasts. The coefficient on *LOSS* is significant for all tests indicating that financial analysts are less accurate and more dispersed for firms that experience a loss in the current period. Prior literature demonstrates that financial analysts in some cases fail to predict failures and as a result, firms with losses are more likely to be associated with negative earnings surprises (Skinner & Sloan, 2001; Kinney, Burgstahler, & Martin, 2002).

The Δ *EARN* control is highly significant for all tests. The negative sign for tests with *AFEP* as the dependent variable suggests that larger absolute increases in earnings from the prior period are associated with less accurate forecasts of future earnings. *HORIZ* is significant

in both tests of dispersion, indicating that shorter time periods between forecasts and earnings disclosures leads to more accuracy and less dispersion. Finally, as predicted the *VOL* control is significant in both tests. *VOL* represents the volatility in a firms reported earnings, thus a negative result for tests involving forecast accuracy indicate that a lack of smooth earnings from year to year increases the likelihood of forecast inaccuracy and a positive result for tests involving dispersion indicate that a lack of smooth earnings increases forecast dispersion.

Panel A of Table 4 shows the results of estimating equation (5). The first two columns of results provide the results of estimating equation (5) with *AFEP* as the dependent variable, while the final two columns provides the results of the same models with *DISP* as the dependent variable. Note that, as predicted, the coefficient on *CR* are positive and significant at the one percent level for the test with *AFEP* as the dependent variable indicating that higher levels of *CR* are associated with more financial analyst forecast accuracy. This result supports Hypothesis 2 and indicates that financial analysts produce more accurate earnings forecasts for firms with higher credit ratings. Similarly, for the test with *DISP* as the dependent variable, the coefficient on *CR* is negative and significant. This also supports Hypothesis 2 and indicates that financial analysts' earnings forecast estimates are less dispersed for firms with higher credit ratings.

Table 4

Rating with <i>AFEP</i> and <i>DISP</i> including <i>EQ</i>				
Independent Variable	Panel A Dependent variable: <i>AFEP</i>		Panel B Dependent variable: <i>DISP</i>	
	Coefficient	Coefficient	Coefficient	Coefficient
<i>Intercept</i>	-0.0629	-0.4636 ***	0.0069 ***	0.0100 ***
<i>CR</i>	0.0352 ***	0.0674 ***	-0.0007 ***	-0.0010 ***
<i>EQ</i>	0.9469 **	19.4343 ***	-0.0183 ***	-0.1617 ***
<i>CR*EQ</i>		-1.4310 ***		0.0111 ***
<i>FOLLOW</i> ¹	10.2900 ***	10.3000 ***	-0.0173 **	-0.0173 **
<i>LOSS</i>	-1.3173 ***	-1.3158 ***	0.0173 ***	0.0173 ***
<i>ΔEARN</i>	-19.0601 ***	-19.1496 ***	0.2170 ***	0.2177 ***
<i>HORIZ</i> ¹	-3.8300 ***	-3.8400 ***	0.0013	0.0014 *
<i>VOL</i>	-2.2852 ***	-2.4680 ***	0.0758 ***	0.0772 ***
<i>IND</i>	Included	Included	Included	Included
<i>YEAR</i>	Included	Included	Included	Included
<i>Adjusted R</i> ²	0.3350	0.3363	0.4830	0.4837
<i>n</i>	88,652	88,652	88,652	88,652

*, **, *** indicate statistical significance utilizing heteroscedasticity consistent standard errors at the 10%, 5%, and 1% levels, respectively. ¹These coefficients are multiplied by 1,000 for ease of interpretation. *IND* is an industry control using the I/B/E/S industry classification. *YEAR* is an annual control representing the year in which firm j's earnings are reported. All other variables are defined in Table 1.

Also as predicted, the coefficient on *EQ* is positive and significant for the test with *AFEP* as the dependent variable indicating that lower earnings quality, as indicated by higher levels

of *EQ* is associated with more financial analyst forecast accuracy. This result supports Hypothesis 3 and indicates that financial analysts produce more accurate earnings forecasts for firms with lower earnings quality due to their management of earnings to match financial analysts' earnings expectations. Similarly, for tests with *DISP* as the dependent variable, the coefficient on *EQ* is negative and significant. This also supports Hypothesis 3 and indicates that financial analysts' earnings forecast estimates are less dispersed for firms with lower earnings quality and therefore more dispersed for firms with better earnings quality.

Consistent with prior literature, *FOLLOW* is significant in all four tests indicating that when more financial analysts follow a firm, financial analysts are more accurate and are less dispersed in their earnings forecasts. The coefficient on *LOSS* is significant for all tests indicating that financial analysts are less accurate and more dispersed for firms that experience a loss in the current period. Prior literature demonstrates that financial analysts in some cases fail to predict failures and as a result, firms with losses are more likely to be associated with negative earnings surprises (Skinner & Sloan, 2001; Kinney, Burgstahler, & Martin, 2002).

The $\Delta EARN$ control is highly significant for all tests. The negative sign for tests with *AFEP* as the dependent variable suggests that larger absolute increases in earnings from the prior period are associated with less accurate forecasts of future earnings. Recall that $\Delta EARN$ is the absolute value of the change in earnings per share from the previous year scaled by price. This result is likely due to financial analysts' uncertainty when faced with large changes in earnings from one period to the next. *HORIZ* is not significant in our tests of dispersion, but consistent with prior literature is significant for tests involving accuracy. Finally, as predicted the *VOL* control is significant in all tests. *VOL* represents the volatility in a firm's reported earnings, thus a negative result for tests involving forecast accuracy indicate that a lack of smooth earnings from year to year increases the likelihood of forecast inaccuracy and a positive result for tests involving dispersion indicate that a lack of smooth earnings increases forecast dispersion.

Table 4 also provides the results of estimating equation (6), which includes the interaction of credit ratings with earnings quality ($CR*EQ$). As in our prior test, the main effect of *CR* is positive and significant (0.0352, $p < 0.0001$). Note that all the control variables' direction and significance are also consistent with the prior test. The $CR*EQ$ interaction term is negative and significant (-1.4310, $p < 0.0001$) indicating that the quality of reported earnings affects the influence that credit ratings have on forecast accuracy. Specifically, at higher levels of credit ratings, the negative association between earnings quality and financial analyst forecast accuracy is reduced. This result is consistent with our expectations regarding the moderating effect that earnings quality has on the relationship between credit ratings and financial analyst forecast accuracy and provides evidence for the moderating effect of earnings quality anticipated by Hypothesis 4.

The results with *DISP* as the dependent variable similarly support our hypothesis regarding the moderating effect of earnings quality. For the test involving forecast dispersion, the

$CR*EQ$ interaction term is positive and significant (-0.1617 , $p < 0.0001$) indicating that the quality of reported earnings affects the influence that credit ratings have on forecast accuracy. Specifically, at higher level of credit ratings, the positive association between earnings quality and financial analyst forecast dispersion is reduced. This result is also consistent with our expectations for Hypothesis 4 regarding the moderating effect that earnings quality has on the relationship between credit ratings and financial analyst forecast accuracy.

For each of our tests that do not include interaction variables in Table 4, the variance inflation factors for all of the independent variables are less than 4, indicating low levels of multicollinearity among the independent variables.⁶ We also test the null hypothesis that there is constant variance of the residuals using the White test for all models. We find that heteroscedasticity is present and we therefore calculate all significance levels for our tests using heteroscedasticity consistent standard errors. Additionally, we test for autocorrelation and find evidence that the residuals may not be independent. We therefore re-estimate our model correcting for autocorrelation and find similar results.

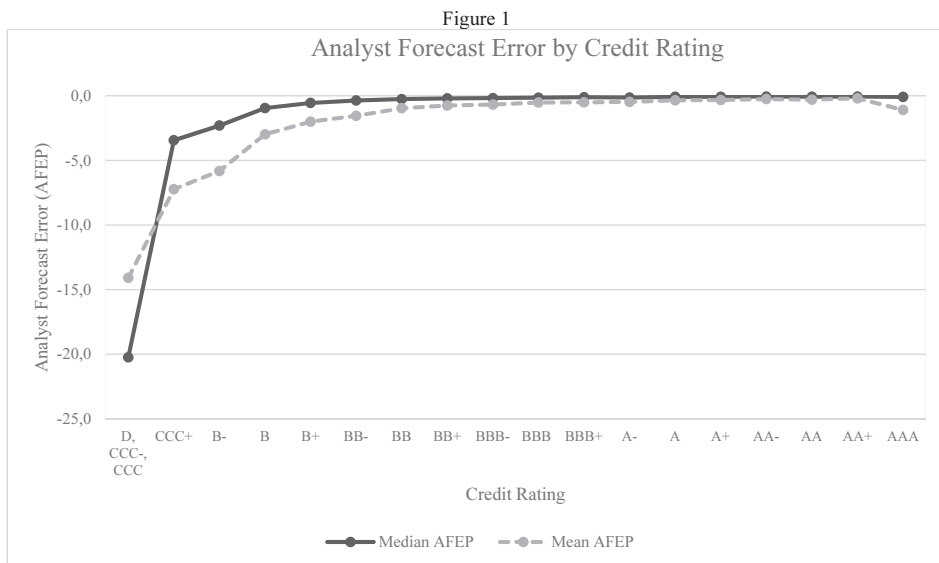


Figure 1 provides further analysis of the relationship between credit ratings and analyst forecast accuracy. Figure 1 shows an increase in analyst forecast accuracy as the credit rating of a firm increases. The increase in accuracy is most pronounced from the lowest ratings which are “D, CCC-, CCC” which have a median *AFEP* value of -20.248 to “CCC+” ratings which have a median *AFEP* value of -3.4464 .⁷ However, increases in

⁶ The largest variance inflation factors in these models occur among the industry control dummy variables with the largest value at 3.3. The variance inflation factor for all other independent variables is less than 2.

⁷ We combine firms with a “D”, “CCC-”, or a “CCC” rating due to the small number of firms that receive these ratings. Only a combined 77 of the 88,652 observations with a credit rating in our sample received one of these three ratings. In contrast, 452 firms received a “CCC+” rating.

accuracy continue throughout each of the non-investment grade ratings to firms with a “BB+” rating which have a median *AFEP* value of -0.2039. There is much less variation in investment grade ratings as “BBB-” rated firms have a median *AFEP* value of -0.1860 and firms with a “AAA” rating have a median *AFEP* value of -0.0944 with no investment grade rated firm having a median *AFEP* value of more than -0.0661. While there is not as much improvement in forecast accuracy as credit ratings improve for investment grade firms, there is dramatic improvement in forecast accuracy among non-investment grade firms as credit ratings increase. Overall, across all credit ratings, Figure 1 shows that as credit ratings increase, there is a clear increase in forecast accuracy.

5. ADDITIONAL ANALYSES AND SENSITIVITY TESTS

In order to test the sensitivity of our results to alternative measure for certain variables, we perform four additional tests. First, we use smoothness as an alternative measurement of earnings quality. Second, we utilize credit rating changes instead of the actual credit rating as an alternative specification. Third, we test for endogeneity using Granger causality tests. Last, we replicate our testing using alternative specifications of analyst forecast accuracy.

5.1. Smoothness as a Measure of Earnings Quality

We replicate our results using smoothness as an alternative measure of earnings quality to test the consistency of reported earnings. As in prior literature (e.g. Leuz, Nanda, & Wysocki, 2003; Gao & Zhang, 2015), we compute smoothness of earnings as follows:

$$SMOOTH_{j,t} = \frac{\sigma(NI / ASSETS)_{j,t}}{\sigma(CFO / ASSETS)_{j,t}} \quad (6)$$

where for firm j and at time t :

σ	= standard deviation over the most recent 5 year period
NI	= net income
CFO	= cash flow from operations
$ASSETS$	= total assets.

Because higher levels of variance in earnings relative to cash flows indicate that a firm's earnings are more volatile, higher levels of *SMOOTH* indicate lower levels of earnings smoothness. Conversely, lower levels of variance in earnings relative to cash flows indicate that earnings are more consistent. Therefore, lower levels of *SMOOTH* indicate higher levels of earnings smoothness. As consistent earnings are a desirable earnings attribute (Graham, Harvey, & Rajgopal, 2005), firms may manipulate earnings to achieve a smooth earnings path. As is the case with overall earnings quality, this manipulation of earnings can increase the uncertainty of the forecasting environment and increase the difficulty of the forecasting environment leading to a reduction in financial analyst forecast

accuracy and more dispersion among financial analyst forecasts. Therefore, we expect that *SMOOTH* will have a negative effect on financial analyst accuracy or *AFEP* and a positive effect on *DISP*.

Table 5

Rating with AFEP and DISP including SMOOTH					
Independent Variable	Panel A		Panel B		
	Dependent variable: <i>AFEP</i>		Dependent variable: <i>DISP</i>		
	Coefficient	Coefficient	Coefficient	Coefficient	
<i>Intercept</i>	0.0272	0.5913 ***	0.0062 ***	0.0032 ***	
<i>CR</i>	0.0370 ***	-0.0016	-0.0007 ***	-0.0005 ***	
<i>SMOOTH</i>	-0.0974 ***	-0.4565 ***	0.0001	0.0020 ***	
<i>CR*EQ</i>		0.0258 ***		-0.0001 ***	
<i>FOLLOW</i> ¹	9.1900 ***	9.2200 ***	-0.0159 *	-0.0160 *	
<i>LOSS</i>	-1.2732 ***	-1.2190 ***	0.0173 ***	0.0170 ***	
<i>ΔEARN</i>	-19.2472 ***	-18.9791 ***	0.2169 ***	0.2155 ***	
<i>HORIZ</i> ¹	-3.8200 ***	-3.8000 ***	0.0013	0.0012	
<i>VOL</i>	0.4150	0.2987	0.0703 ***	0.0709 ***	
<i>IND</i>	Included	Included	Included	Included	
<i>YEAR</i>	Included	Included	Included	Included	
<i>Adjusted R</i> ²	0.3369	0.3434	0.4828	0.4845	
<i>n</i>	88,652	88,652	88,652	88,652	

*, **, *** indicate statistical significance utilizing heteroscedasticity consistent standard errors at the 10%, 5%, and 1% levels, respectively. ¹These coefficients are multiplied by 1,000 for ease of interpretation. *IND* is an industry control using the I/B/E/S industry classification. *YEAR* is an annual control representing the year in which firm *j*'s earnings are reported. All other variables are defined in Table 1.

When substituting the *SMOOTH* variable for *EQ* in our equations (5) and (6), we find that, with the exception of the result for the *VOL* control, our results are consistent with Table 4. Our results in Table 5 demonstrate that firms with higher credit ratings and smoother earnings are associated with more accurate financial analyst forecasts. In Table 5, we also find some evidence that higher credit ratings and smoother earnings are associated with less forecast dispersion. While in our tests of equation (5) only higher credit ratings are associated with lower forecast dispersion, our tests of equation (6) show that both higher credit ratings and smoother earnings are both associated with less forecast dispersion. Additionally, we find that our tests regarding the interaction between credit ratings and earnings smoothness and its effect on accuracy and dispersion remain significant. Specifically, at higher level of credit ratings, both the negative association between earnings quality and financial analyst forecast accuracy and the positive association between earnings smoothness and financial analyst forecast dispersion are reduced. Taken together with our results from Table 4, our results when substituting *SMOOTH* for *EQ* in our equations (5) and (6), we find further evidence for Hypotheses 2, 3, and 4.

5.2. Change in Credit Rating

In some cases, prior literature utilizes the change in credit rating to study external reports of a firm's financial position (Ederington & Goh, 1998); therefore we replicate our results utilizing this measure in place of the firm's current rating.

Table 6

Change in rating with AFEP and DISP including EQ				
Independent Variable	Panel A		Panel B	
	Dependent variable: <i>AFEP</i>		Dependent variable: <i>DISP</i>	
	Coefficient	Coefficient	Coefficient	Coefficient
Intercept	0.3454 ***	0.3501 ***	-0.0020 ***	-0.0019 ***
ΔCR	0.2373 ***	0.2749 ***	-0.0026 ***	-0.0022 ***
<i>EQ</i>	0.5205	0.5547	-0.0107 ***	-0.0103 ***
<i>CR*EQ</i>		-1.8085 *		-0.0214 **
<i>FOLLOW</i> ¹	13.6500 ***	13.5600 ***	-0.0907 ***	-0.0917 ***
<i>LOSS</i>	-1.2904 ***	-1.2955 ***	0.0177 ***	0.0176 ***
$\Delta EARN$	-19.1504 ***	-19.1763 ***	0.2209 ***	0.2206 ***
<i>HORIZ</i> ¹	-3.8500 ***	-3.8500 ***	0.0018 **	0.0018 **
<i>VOL</i>	-3.1104 ***	-3.0802 ***	0.0910 ***	0.0914 ***
<i>IND</i>	Included	Included	Included	Included
<i>YEAR</i>	Included	Included	Included	Included
<i>Adjusted R</i> ²	0.3381	0.3382	0.4833	0.4833
<i>n</i>	88,652	88,652	88,652	88,652

*, **, *** indicate statistical significance utilizing heteroscedasticity consistent standard errors at the 10%, 5%, and 1% levels, respectively. ¹These coefficients are multiplied by 1,000 for ease of interpretation. *IND* is an industry control using the I/B/E/S industry classification. *YEAR* is an annual control representing the year in which firm *j*'s earnings are reported. All other variables are defined in Table 1.

Our results in Table 6 indicate that our results regarding the relationships between credit ratings, earnings quality and forecast accuracy as well as forecast dispersion are essentially unchanged. The significance level of the interaction variables decreases, but remains consistent. These results again confirm Hypotheses 2, 3, and 4 regarding the association between financial analysts' forecasts and firm credit ratings and earnings' attributes.

5.3. Endogeneity between Credit Ratings and Financial Analyst Forecast Performance

As outlined above, we expect that firms with higher credit ratings allow for financial analysts to make their earnings forecast for a firm with more accuracy and less uncertainty. However, the possibility exists that financial analyst activity itself could have an effect on the credit ratings that are issued. For example, Cheng and Subramanyam (2008) find that a reduction in financial analysts following a firm leads to a decrease in credit ratings. Similarly, Mansi, Maxwell, and Miller (2011) find that an increase in financial analyst activity leads to a decrease in credit yields. Therefore, it is possible that an endogenous relationship exists between credit ratings and financial analyst forecast accuracy and dispersion. We examine

this possibility by performing Granger causality tests to explore the connection between financial analyst activity and credit ratings. In untabulated results, we find results similar to those of Ederington and Goh (1998), in that Granger causality flows both ways. Our testing demonstrates significant results when regressing forecast accuracy on both prior period credit ratings and prior period forecast accuracy. At the same time, we also find significant results when regressing credit ratings on both prior period forecast accuracy and prior period credit ratings. While these results provide some evidence that credit ratings have an effect on performance of financial analysts, financial analyst activity also can have a simultaneous effect on the reports issued by credit rating agencies.

5.4. Alternative Measures of Analyst Forecast Accuracy

We replicate our results using several alternate measures of forecast accuracy to test the sensitivity of our results to other measures of analyst forecast accuracy. First, we replicate our results using two alternate measures in the numerator. Prior literature has utilized a log transformation to reduce skewness in variables (Nikolaev 2010). Therefore, we begin our alternate measurement analysis by computing the natural log of the difference between the analyst forecast and the net income of the firm (*LNAFEP*).⁸ We replicate our tests using this alternate measurement as follows:

$$LNAFEP_{i,j,t} = \frac{\ln(1000 * (FORECAST_{i,j,t}^{t-1} - NI_{j,t}))}{PRICE_{j,t}} (-1) \quad (7)$$

where for analyst *i*, firm *j*, and at time *t*:

<i>FORECAST</i>	= forecasted net income
<i>NI</i>	= reported net income
<i>PRICE</i>	= stock price.

Consistent with Bradshaw et al. (2016) we compute analyst forecast error utilizing the squared difference between the analyst forecast and the net income of the firm (*SQAFEP*). Therefore, we replicate our results utilizing the following substitute measure:

$$SQAFEP_{i,j,t} = \frac{(FORECAST_{i,j,t}^{t-1} - NI_{j,t})^2}{PRICE_{j,t}} (-100) \quad (8)$$

where for analyst *i*, firm *j*, and at time *t*:

<i>FORECAST</i>	= forecasted net income
<i>NI</i>	= reported net income
<i>PRICE</i>	= stock price.

⁸ Although, for interpretative purposes, we multiply all other forecast error equations in this study by (-100), because of the diminutive values resulting by the log transformation in equation 7, note that we multiply the numerator by 1000, and therefore multiply the forecast error by (-1).

Additionally, we check the consistency of our results by scaling the computation of the difference between the analyst forecast and the net income of the firm with earnings per share instead of price in the denominator (Collins, Hopwood, & McKeown, 1984). Utilizing earnings per share to scale analyst accuracy, we compute forecast error (*EPSAFEP*) as follows:

$$EPSAFEP_{i,j,t} = \frac{|FORECAST_{i,j,t}^{t-1} - NI_{j,t}|}{EPS_{j,t}} (-100) \quad (9)$$

where for analyst i , firm j , and at time t :

<i>FORECAST</i>	= forecasted net income
<i>NI</i>	= reported net income
<i>EPS</i>	= reported earnings per share.

Overall, when utilizing these three alternative specifications of analyst forecast accuracy, we find largely similar results. For example, when testing our results utilizing the natural log of the differences between analyst forecasts and earnings (*LNAFEP*) as a part of equation (5), in untabulated results the coefficient of *CR* remains positive and significant at one percent indicating that higher accuracy in analysts' forecasts of earnings is associated with firms that have higher credit ratings. Further, the coefficient of *EQ* remains positive and significant, but the level of significance drops from five percent to ten percent. When utilizing the alternative specification *SQAFEP* that determines analyst forecast error by calculating the squared difference between the forecast and the actual earnings, in untabulated results we find that the correlation between *SQAFEP* and *CR* is positive and significant. However, when *SQAFEP* is included as the dependent variable in equation (5), the coefficient on *CR* is negative and significant. In further testing, after winsorizing each of the continuous variables at 5%, and testing again *SQAFEP* as the dependent variable in equation (5), the coefficient on *CR* is again positive and significant at 1% indicating that outliers are the cause of our spurious results in the initial test of *SQAFEP* in equation (5). Finally, when replicating our results with earnings per share as an alternate to share price in the denominator of the measure as described above (*EPSAFEP*) in equation (5), in untabulated results the results are consistent with our main tests as we find that the coefficient on *CR* is positive and significant at 1% and the coefficient on *EQ* is positive and significant at 5%.

6. SUMMARY AND CONCLUSION

Using models of forecast performance from prior literature, we examine the relationship of credit ratings with the accuracy of financial analysts' forecasts and the dispersion of forecasts. Controlling for factors that are known in the literature to introduce task complexity into the forecasting environment, we hypothesize that high credit ratings are associated with more accurate and less dispersed earnings forecasts. This study provides several new results. First, we find that the existence of a firm's credit ratings during the

forecasting horizon has a significant impact on the accuracy and dispersion patterns of financial analysts' earnings forecasts. Second, we find that higher credit ratings are associated with more accurate forecasts and less dispersed forecast patterns. Next, we find that the level of a firm's earnings quality moderates the effect that credit ratings have on analyst performance. This particular result suggests that the coexistence of high credit ratings and high quality earnings reports provides a less complex and more forecast-friendly environment. In additional testing we use three alternate specifications of forecast accuracy to repeat our tests. The results of these alternate tests are consistent with our primary findings.

This study is motivated by making contributions that provide 1) analysts with confirmation of the usefulness of credit ratings in assessing future earnings, 2) regulators with further evidence of the importance of high quality earnings reports, 3) investors with the knowledge that future earnings forecasts are likely more accurate for a firm with higher credit ratings, and 4) researchers with additional insights of the determinants of financial analyst forecasting performance. Additionally, these results also add to the body of literature that illustrates how task complexity hinders the predictive value of earnings reports.

Our results allow for related future research in several ways. First, future studies could explore the link between credit ratings and changes in financial analysts' performance based on whether it is classified as investment grade, speculative grade, or other various subcategories. Second, future studies could utilize measures of relative analyst forecast accuracy to determine whether there is an interactive effect between credit ratings and specific analyst characteristics, such as analyst experience, on their performance. Finally, extensions of this research could examine whether and to what degree the level of credit ratings interact with other variables known in the literature to have a significant impact on forecast accuracy and dispersion.

Our research is subject to certain limitations. As we have reported in our testing, while we find that credit ratings have an effect on financial analyst performance, there is also a simultaneous effect that financial analysts' earnings forecasts may have on credit ratings themselves. Additionally, the Compustat database utilized in this study includes Standard & Poor's credit ratings exclusively and thus future research could duplicate our testing with data from all rating agencies. Finally, although we use controls in our testing that are common for this area in the literature, as is the case in all empirical research our models may be misspecified due to the possibility of omitted control variables.

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