The Information Role of Earnings Quality in Management Forecast Activity

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ABSTRACT: Motivated by voluntary disclosure theory, I examine the relation between innate and discretionary earnings quality and management's earnings forecast decisions. I argue that high innate earnings quality implies managers have high quality information simply because of firm characteristics and therefore requires relatively low effort to attain and bears low proprietary costs of disclosure. Conversely, high discretionary earnings quality reflects information that requires management exert relatively high effort to attain and carries high proprietary costs. Therefore, disclosure theory suggests managers are more likely to forecast earnings when innate earnings quality is high (i.e., a complementary relation), but less likely when discretionary earnings quality is high (i.e., a substitutive relation). I find evidence consistent with these predictions. Further, the complementary relation between innate earnings quality and forecast activity is stronger for firms with higher levels of institutional ownership and greater commitment to financial statement verification, suggesting these previously documented disclosure influences exacerbate the effect of innate earnings quality. My results are consistent with and help reconcile prior theoretical and empirical research supporting both complementary and substitutive relations between earnings quality and managers' voluntary disclosure decisions.

Keywords: Management Forecast, Earnings Quality, Information Quality, Voluntary Disclosure

JEL Classification: M40, M41, G30

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1. Introduction

Identifying determinants of voluntary disclosure, especially those related to a firm's forecasting decisions, represents one of the most widely researched topics in empirical accounting research (e.g., Imhoff Jr 1978; Waymire 1985; Coller and Yohn 1997; Ajinkya et al. 2005; Karamanou and Vafeas 2005; Lennox and Park 2006; Feng et al. 2009; Baik et al. 2011; Ball et al. 2012). A sizable subset of this research examines how properties of a firm's earnings and related disclosures correlate with management forecast activity (e.g., Imhoff Jr 1978; Waymire 1985; Lennox and Park 2006; Feng et al. 2009; Ball et al. 2012). I explore the role of earnings quality (EQ), defined as the degree of estimation error in a firm's earnings (Dechow and Dichev 2002; McNichols 2002), in management's forecast decisions. Further, I predict that components of EQ (innate vs. discretionary) have opposite effects on management forecast activity.[1]

The quality of a firm's earnings may affect voluntary disclosure decisions for three reasons. First, EQ provides a signal of the quality of a firm's information (Francis et al. 2008). Theoretical work on voluntary disclosure models how information quality impacts the propensity of firms to voluntarily disclose, yielding two alternative predictions (e.g., Verrecchia 1983; Verrecchia 1990; Penno 1997; Nagar 1999). Higher information quality may lead to more voluntary disclosure since the usefulness of the disclosure to investors increases with the quality (reliability) of the underlying information (Verrecchia 1990; Nagar 1999). Alternatively, disclosure and information quality may substitute for one another if managerial effort needed to observe a high quality signal is too great (Penno 1997) or the release of high quality information bears greater costs of disclosure (Verrecchia 1983). Second, prior research suggests that firms with poorer EQ experience greater information asymmetry (e.g., Bhattacharya et al. 2012). If voluntary disclosure is a response to information asymmetry (Diamond and Verrecchia 1991), then poor EQ may lead to increased voluntary disclosure. Third, earnings having fewer estimation errors, or higher EQ, are presumably more value relevant for investors since they better communicate expected future cash

[1] Following prior research, innate EQ represents the proportion of accrual estimation errors attributable to firm characteristics out of a manager's short-term control, while discretionary EQ reflects accuracy in accruals attributable to managerial choices and skill. I discuss these concepts more in Section 2.4.

flows. Thus, earnings related disclosures, such as management forecasts, are also more useful for firms with more value relevant earnings. Consistent with this conjecture, Lennox and Park (2006) show that firms with more value relevant earnings issue more frequent forecasts.[2]

While extant empirical research considers the effects of the value relevance of earnings and information asymmetry on management's forecasting decisions (e.g., Waymire 1985; Coller and Yohn 1997; Lennox and Park 2006), the literature fails to consider the role of the information quality signal provided by a firm's EQ. I address this gap by isolating the information quality signal of EQ. More importantly, I investigate whether the nature of the relation between innate EQ and management forecasts and discretionary EQ and forecasts differs because each component of EQ provides a different signal to investors about the quality of managers' private information. Dechow and Dichev (2002) and Francis et al. (2004; 2005) identify several institutional firm features that affect a firm's EQ. Francis et al. (2004) use these features to decompose EQ into innate and discretionary components. In other words, the degree of estimation error in a firm's earnings varies with both innate firm characteristics largely out of managers' short-term control and managerial discretion (McNichols 2002). I argue that the nature of these components provides insight into the source of a firm's information quality. Specifically, high innate EQ signals managers have high quality information because of firm characteristics, while high discretionary EQ indicates managers take some action that improves the quality of a firm's information environment. These actions require greater effort and potentially carry greater costs of disclosure. The differing nature of these signals yields opposite theoretical predictions—high innate EQ leads to more

[2] These three roles of EQ in voluntary disclosure decisions are not unrelated. However, each element affects managers' disclosure decisions for slightly different reasons. Theory suggests that information quality influences disclosure choice through its effect on the benefit (to investors) and costs (to the firm) of disclosure. On the other hand, the incentive to reduce information asymmetry with more voluntary disclosure arises primarily from cost of capital benefits (Diamond and Verrecchia 1991; Botosan 1997; Botosan and Plumlee 2002). Finally, while the rationale for why increased value relevance leads to more earnings-related disclosures is similar to that of information quality, the two characteristics—value relevance of earnings and information quality—are not synonymous. For instance, firm characteristics distinct from information quality, like industry membership, life-cycle, conservatism, and smoothness, affect the value relevance of earnings (Amir and Lev 1996; Barton et al. 2010). Thus, while related, the underlying rationale for why information quality, information asymmetry, and value relevance affect disclosure differ.

disclosure, or a complementary association, while high discretionary EQ makes disclosure costly, yielding a substitutive relation.

To test these hypotheses, I employ three measures of management forecast activity: forecast occurrence, frequency, and horizon of the first forecast for a given year's earnings.[3] To proxy for EQ, I quantify accrual estimation errors using a modified version of the frequently employed model of accruals quality (Dechow and Dichev 2002; McNichols 2002), which I decompose into innate and discretionary components as in Francis et al. (2004). My modification is to introduce a Box-Cox (1964) power transformation of total accruals quality in my decomposition model to minimize correlation between components. Correlation between components may reflect measurement error in each component, which leads to an alternative explanation for my results.[4] In addition, I control for information asymmetry and the value relevance of earnings to increase the likelihood that my results are distinct from those documented in prior research.

In general, I find results consistent with my hypotheses. Controlling for the value relevance of earnings and information asymmetry, I find that innate EQ positively relates to forecast occurrence, frequency, and horizon, consistent with firms complementing high quality information with more disclosure. Alternatively, I find a significantly negative relation between discretionary EQ and all three measures of forecast activity, consistent with the notion that information attainment and disclosure costs increase with discretionary EQ, thus lessening the level of disclosure.

My final analyses examine whether two other factors found to affect managers' disclosure activity vary with innate EQ. Prior research suggests firms with high levels of institutional ownership issue more forecasts, presumably because these investors exert greater influence over management

[3] I focus on measures of forecast activity rather than bias or accuracy for two reasons. First, disclosure theory generally refers to the decision to disclose or not disclose, which maps more closely to measures of forecast activity than to estimates of error or bias in individual forecasts. Second, my motivation for why forecast activity substitutes for discretionary EQ does not necessarily extend to forecast errors. Namely, once a firm decides to issue a forecast, it is unclear why discretionary EQ would substitute for (or reduce) forecast accuracy.

[4] I discuss this in more detail in Section 3 and Appendix 2. To summarize, this transformation procedure reduces rank correlation between EQ components from -0.34 in the untransformed model to an insignificant 0.005 in the transformed model, minimizing the likelihood that measurement error provides an alternative explanation for my results.

(Ajinkya et al. 2005; Karamanou and Vafeas 2005). Similarly, Ball et al. (2012) find that external verification of financial statements, measured by abnormal audit fees, relates positively to management forecast frequency (and accuracy), likely because auditors enhance the reliability of information underlying these disclosures.[5] I contend that the complementary relation between innate EQ and forecast activity increases with both institutional ownership and external verification of financial statements because the information underlying forecasts of high (low) innate EQ firms is more (less) informative. Consistent with these predictions, I find that the complementary association between forecast occurrence, frequency, and horizon is greater for firms with higher levels of institutional ownership. Further, I find that the complementary relation between innate EQ and management forecast frequency is higher for firms with greater abnormal audit fees, though this result does not extend to forecast occurrence or horizon.

My primary contribution to the literature is that I show that simply assessing the association between total EQ and management forecasts, and possibly other measures of voluntary disclosure, obfuscates the true relation. Whereas Francis et al. (2008) conclude that EQ complements voluntary disclosure and has a first order effect on a firm's cost of equity, they recognize that "further work is needed to fully explain conflicting evidence in the literature concerning relationships among these constructs" (Francis et al. 2008, 55). Focusing on two of these constructs, EQ and voluntary disclosure, I predict and find a simultaneously complementary and substitutive association. Further, my results show that theories prescribing complementary and substitutive relations between information quality and disclosure choice need not be mutually exclusive.

In addition, I extend the management forecast literature by simultaneously testing multiple roles of EQ in disclosure demands. Accounting researchers have long been interested in why firms selectively provide earnings guidance, and "identifying the factors affecting management's voluntary disclosure

[5] I recognize that other research takes a different view of abnormal audit fees. For instance, Hribar et al. (2013) use abnormal audit fees as an inverse measure of accounting quality, a very different characterization than in Ball et al. (2012). I leave reconciling these two views of abnormal audit fees to future research.

decisions is a fundamental research problem with implications for policy makers, the business community, and academics" (Karamanou and Vafeas 2005, 454). I contribute to this fundamental research problem by showing that disclosure activity varies with three features of a firm's information environment reflected in EQ: information asymmetry, the value relevance of earnings, and information quality.

The remainder of this paper is as follows: Section 2 discusses prior research and provides motivation for my hypotheses. Section 3 presents my research design, followed by results in Section 4. Section 5 concludes.

2. Background Literature, Motivation and Hypothesis Development

2.1 Information quality and management forecasts

The relation between information quality and voluntary disclosure decisions, such as those related to management's forecasts of earnings, has long been the subject of theoretical research in accounting, finance, and economics. Early theory predicts full disclosure of private information because of the unraveling principle (Grossman and Hart 1980; Milgrom 1981). Unraveling implies that firms respond to information asymmetry with full disclosure because investors interpret nondisclosure as an admission by management that the asset (firm) is worth some minimum possible value.[6] This theory suggests managers of all firms should make frequent forecasts of future earnings as new information becomes available. However, extensive empirical evidence shows that managers selectively disclose (see, for example, Givoly and Palmon 1982; Patell and Wolfson 1982; Chambers and Penman 1984; Kothari et al. 2009), leading to subsequent theory attempting to explain cross-sectional variation in disclosure practices. This research collectively yields two conflicting predictions, which I refer to as the complementary and substitutive hypotheses.[7] I discuss each in turn.

[6] These theories assume disclosure must be truthful. There are theoretical models which allow for non-truthful disclosure (e.g. Milgrom and Roberts 1986; Rajan and Sarath 1996; Fischer and Stocken 2001).
[7] This is the same terminology used in Francis et al. (2008).

The complementary hypothesis predicts that firms with higher quality information issue more frequent disclosures. In other words, information quality complements disclosure (and vice-versa). Supporting this prediction, Verrecchia (1990) concludes that firms only disclose when the usefulness of the potential signal exceeds some minimum threshold. This disclosure threshold declines as information quality increases because disclosure originating from higher quality information garners more certain belief revision.[8] Put simply, investors value reliable information more than unreliable information. Nagar (1999) also supports the complementary hypothesis. His model suggests that managers avoid voluntary disclosure because of uncertainty in how the market reacts to unexpected disclosure. However, this unwillingness to disclose decreases as the quality of managers' information increases because increased information quality diminishes uncertainty, implying a higher likelihood of disclosure. Dye (1985) and Jung and Kwon (1988) support the complementary hypothesis as long as investors recognize the quality of managers' information. Specifically, investors assess the likelihood managers are informed as an increasing function of information quality and escalate demand for disclosure accordingly. To summarize, theory supporting the complementary hypothesis suggests that, compared to poor information quality, high quality information makes disclosures more useful to investors and reduces possible misinterpretation, both of which make disclosure more likely. Further, if investors recognize the quality of managers' private information, they demand more disclosure from managers with better information.

Opposite the complementary hypothesis, the substitutive hypothesis predicts that in certain circumstances, greater information quality reduces the likelihood or willingness of firms to voluntarily disclose. Verrecchia (1983) suggests firms face non-zero costs of disclosure and posits that these proprietary costs raise the threshold for disclosure because revelation of certain information carries significant economic penalties. The presence of disclosure costs impedes unraveling as investors recognize that nondisclosure may reflect cost avoidance. Consistent with this view, Graham et al. (2005) report that surveyed executives generally prefer disclosing information pertaining to firm value, such as a

[8] There do exist scenarios when this is not the case. Specifically, if the quality of information affects expected values of realized outcomes nonlinearly, then the threshold for disclosure could decrease as information quality decreases, which yields the opposite relation (Verrecchia 1990).

forecasts of earnings, but they are reluctant to release competitively sensitive information. If higher quality information bears greater proprietary costs (Berger 2011), then it may substitute for voluntary disclosure.[9] However, even absent proprietary costs, investors may not demand disclosure of high quality information if they believe that this information is more costly to obtain than low quality, less precise information (Penno 1997). In other words, investors assess the likelihood of management observing a signal (or "being informed") as a decreasing function of the precision, or quality, of the signal. Thus, costs of information attainment or disclosure may cause information quality to substitute for disclosure.

2.2 Information quality, earnings quality and management forecasts

Empirically, information quality is difficult, if not impossible, to directly measure, but the quality of a firm's earnings, or the degree of estimation error in accruals, reflects the quality of the information underlying those earnings (Francis et al. 2008). Accruals shift recognition of cash flows to and from adjacent periods (Dechow 1994; Dechow and Dichev 2002), and, in order for these adjustments to be accurate and contribute to higher quality earnings, they presumably arise from higher quality information (Francis et al. 2008).[10] Thus, higher EQ signals managers have higher quality information. This information quality signal suggests EQ may complement or substitute for management forecasts (Verrecchia 1983; Verrecchia 1990; Penno 1997; Nagar 1999).

Assuming EQ provides a signal of managers' information quality, extant empirical management forecast research provides some support for a complementary hypothesis. For instance, Imhoff (1978) finds that firms issuing forecasts have smoother earnings and higher analyst forecast accuracy than non-forecasting firms. If firms with smoother earnings and better analyst forecast accuracy tend to have

[9] While I use Verrecchia (1983) and Verrecchia (1990) to motivate different hypotheses, the two papers do not contradict one another. The earlier paper focuses on the role of proprietary costs in disclosure decisions, while the latter examines the role of information quality absent proprietary costs.

[10] Opportunistic degradation of EQ may occur on a limited basis, but research suggests it is unlikely to be a widespread phenomenon (Subramanyam 1996; Bowen et al. 2008). Furthermore, capital market benefits of high EQ (Aboody et al. 2005; Francis et al. 2004; Francis et al. 2005) provide little incentive for managers with high quality information to vitiate the quality of the earnings signal. Finally, in my empirical tests I include controls for governance mechanisms, which at least partially controls for potential opportunism.

higher EQ, then disclosure in the form of forecasts is likely increasing in information quality.[11] Similarly, Waymire (1985) finds that firms with less volatile earnings, a frequently used measure of EQ (e.g., Francis et al. 2004; Francis et al. 2008), issue more frequent and earlier forecasts. Cox (1985) finds that larger firms, which presumably have higher EQ (Francis et al. 2004; Francis et al. 2005), more likely issue forecasts. Lennox and Park (2006) show that firms with more informative earnings, measured by historical earnings response coefficients, provide more forecasts. Finally, Feng et al. (2009) associate higher internal control quality, indicative of higher quality accruals (Doyle et al. 2007), with better disclosure practices.[12]

Research supporting a substitutive relation between management forecast activity and EQ is relatively limited. Imhoff (1978) finds a positive relation between systematic risk, a firm characteristic negatively related to EQ (Bhattacharya et al. 2012), and management forecasts, and Ajinkya et al. (2005) find evidence that audit quality is negatively related to forecast specificity.[13] While not related directly to management forecasts, the substitutive hypothesis finds additional supporting evidence in research examining other, non-earnings related disclosure venues. Namely, Lang and Lundholm (1993) find a negative relation between the returns-earnings correlation and analyst-issued disclosure quality ratings (AIMR scores), Tasker (1998) finds a negative association between conference calls and an industry-based measure of earnings usefulness, and Francis et al. (2008) find a negative correlation between conference calls and their measure of EQ.

While information quality likely plays some part in this empirical research, EQ also relates to two other aspects of a firm's information environment, information asymmetry and the value relevance of earnings, which affect forecasting decisions. Information asymmetry may affect forecast decisions because earnings of firms with poor EQ provide less information to market participants, which leads to

[11] Dechow et al. (2010) discuss the positive link between EQ and analyst forecast accuracy. Tucker and Zarowin (2006) find earnings smoothing is positively related to earnings informativeness.
[12] Using an annual report based measure of disclosure quality, Francis et al. (2008) also support the complementary hypothesis.
[13] Ajinkya et al. (2005) also find that an increase in audit quality (changing from non-Big N to Big N auditor) corresponds to an increase in forecast frequency, which supports the complementary hypothesis if auditors enhance the reliability of management's private information.

more information asymmetry between investors and managers (Bhattacharya et al. 2012). If disclosure is a response to information asymmetry (Diamond 1985; Diamond and Verrecchia 1991; Francis et al. 2008), then EQ and management forecast activity may be negatively.[14] While I define EQ as the degree of estimation error in earnings, EQ also captures how relevant earnings are to decision makers. In defining EQ, Dechow et al. (2010) state, "Higher quality earnings provide more information about the features of a firm's financial performance that are relevant to a specific decision made by a specific decision-maker" (Dechow et al. 2010, 344). Assuming the decision-maker is an equity investor, this definition implies that higher EQ makes earnings more value relevant. The value relevance of earnings affects the usefulness of earnings announcements and other earnings-related disclosures (Lennox and Park 2006; Tucker and Zarowin 2006). Thus, if EQ reflects the value relevance of earnings, then EQ and earnings-related disclosures (i.e. management forecasts) may be positively related.

In sum, the management forecast literature sheds light on the association between EQ and management forecast activity, but no prior research attempts to control for the multiple roles EQ in affecting disclosure choice. For instance, the negative relation between earnings volatility and management forecasts (Imhoff Jr 1978; Waymire 1985) can be explained by both value relevance of earnings (volatility inversely relates to the value relevance of earnings) and the information quality signal provided by EQ.

2.3 Hypothesis development

Since theory does not clearly support a positive or negative relation between overall information quality and management forecast activity, I first present a hypothesis pair allowing for either alternative:

H1a: Controlling for information asymmetry and the value relevance of earnings, EQ complements management forecasts.

[14] For management forecasts, this role may seem counterintuitive. Namely, if poor EQ implies earnings provide little information relevant to firm value, the demand for non-earnings related disclosures likely increases whereas the demand for earnings-related disclosures (i.e. management forecasts) may be muted. However, poor EQ also suggests investors struggle with estimates of future cash flows, increasing the usefulness of management forecasts. Thus, even for firms with poor EQ, earnings forecasts likely alleviate some information asymmetry.

H1b: Controlling for information asymmetry and the value relevance of earnings, EQ substitutes for management forecasts.

2.3.1 Innate vs. discretionary EQ and management forecasts

Prior research identifies several innate factors, likely out of managers' short-term control, that contribute to the quality of a firm's earnings and, more primitively, the quality of management's private information. These factors include firm size, cash flow and sales volatility, the length of the operating cycle, the intensity of capital and intangible assets, and the frequency of operating losses (Dechow and Dichev 2002; Francis et al. 2004; Francis et al. 2005). Larger firms likely have more advanced accounting systems, which enhance the quality of information available to managers, thus resulting in higher EQ. Alternatively, firms with high cash flow or sales volatility, or with long operating cycles likely operate with more inherent uncertainty, reducing the quality of information available to managers. Finally, recurring losses may degrade the ability of earnings to provide information about future prospects (Hayn 1995). These characteristics affect estimation error in accruals, which is manifested in EQ. I refer to the degree of estimation error attributable (not attributable) to these inherent firm traits as innate (discretionary) EQ.

In order for the complementary hypothesis to apply, higher quality information must come at minimal costs of attainment and bear less costs of disclosure. Both of these characteristics likely lead to higher levels of disclosure from firms with high EQ (Dye 1985; Jung and Kwon 1988; Verrecchia 1990). For the substitutive hypothesis to prove descriptive, information attainment and/or disclosure costs must increase with the quality of information (Verrecchia 1983; Penno 1997; Graham et al. 2005). I posit that variation in these cost-related factors coincides with the source of EQ, as innate and discretionary EQ send different signals about the quality of managers' information. This rationale resolves the seemingly contradictory theoretical predictions embodied in the complementary and substitutive hypotheses.

Recall that proprietary costs inhibit the unraveling phenomenon predicted by early disclosure theory (Milgrom 1981; Verrecchia 1983; Verrecchia 2001). If proprietary costs increase with the quality

of information, then firms may be less willing to disclose when information quality is high. However, the effect of proprietary costs on disclosure of information arising from innate firm characteristics may be muted for at least two reasons. First, management likely has little short-term control over these innate firm features (Francis et al. 2008), and, assuming a firm's management generates most of the information that is considered proprietary, it is unlikely this information is reflected in a firm's innate EQ. Second, information quality attributable to innate firm characteristics presumably relates little to opportunity costs, as many inherent traits are similar across firms within an industry.[15] For both of these reasons, I expect proprietary costs to play less of a role in impeding disclosure from firms with high innate EQ.

Penno (1997) suggests that the likelihood of being informed (or the precision of the signal available to managers) may decrease as information quality rises because information of higher quality is harder to obtain. Using this rationale, he also supports the possibility of a negative relation between EQ and disclosure. However, as with proprietary costs, I predict that this effect is less pronounced for innate EQ since acquisition of information arising from innate firm characteristics should require minimal costs of attainment. In fact, holding constant the level of effort to obtain information, managers of firms with high innate EQ should be *more* informed than those with low innate EQ. Thus, investors should not assume the ex-ante probability that management is informed decreases in innate EQ since the cost of information attainment is not rising with this source of information.

To summarize, I argue that innate EQ carries lower proprietary costs due to the nature of its origination and requires minimal managerial effort to realize. Each of these factors increases the likelihood that firms complement high innate EQ with more disclosure. Consistent with this conjecture, I predict a complementary relation between innate EQ and management forecast activity, presented in my next hypothesis:

H2: Controlling for information asymmetry and the value relevance of earnings, innate EQ complements management forecast activity.

[15] To test this conjecture, I regress the natural log of a firm's operating cycle (a determinant of innate EQ) on year and industry fixed effects. I find that these fixed effects explain nearly 70% of variation in operating cycles (untabulated), supporting the notion that innate earnings quality correlates with industry.

Information quality not explained by innate firm characteristics reflects the actions and choices of firm management. I suggest that this component of quality is reflected in a firm's discretionary EQ. The complementary hypothesis requires the benefit of, and therefore demand for disclosure to increase with the quality of the information. Unlike innate EQ, I expect the costs of disclosure to increase with discretionary EQ because the information underlying this component carries greater costs of attainment and disclosure. First, time and effort spent enhancing information quality, reflected in higher discretionary EQ, potentially detracts from that spent preparing and disseminating information via voluntary disclosure. Second, if managers contribute to firm differentiation or a competitive advantage, then opportunity costs are potentially higher for disclosures of information reflected in discretionary EQ). Thus, the threshold for disclosure rises with discretionary EQ (Verrecchia 1983). This rationale leads to my third hypothesis:

H3: Controlling for information asymmetry and the value relevance of earnings, discretionary EQ substitutes for management forecast activity.

2.3.2 Other factors affecting demand for disclosure

Disclosure theory often models the choice to disclose as a response to a demand for disclosure by a firm's investors. Research suggests that institutional investors demand greater transparency, leading to a positive relation between institutional ownership and forecast frequency, specificity, and accuracy (Ajinkya et al. 2005; Karamanou and Vafeas 2005). I posit that higher levels of institutional investors exacerbate the relation between innate EQ and management forecasts since those investors can exert greater influence over a firm's management. This rationale leads to my next hypothesis:

H4: Controlling for information asymmetry and the value relevance of earnings, the complementary relation between innate EQ and management forecast activity is greater for firms with high levels of institutional ownership.

I do not expect this institutional investor effect to extend to discretionary EQ. Even if institutional investors can exert more influence over managers' disclosure choices, costs associated with higher discretionary EQ still deter disclosure.

Auditors provide a second oversight mechanism by providing independent verification of financial statement information. Ball et al. (2012) find that managers committing more resources to financial statement verification (i.e. abnormal audit fees) make more frequent forecasts because increased reliability makes the information more useful to investors. Innate EQ complements voluntary disclosure, and I predict this relation to be even stronger when the underlying information is more reliable. In other words, increased external verification further enhances high quality information, increasing the complementary association between innate EQ and management forecast activity. This rational leads to my final hypothesis:

> **H5:** Controlling for information asymmetry and the value relevance of earnings, the complementary relation between innate EQ and management forecast activity is greater for firms with high levels of external verification (abnormal audit fees).

As with H4, I do not expect the enhanced reliability generated by increased external verification to affect the relation between discretionary EQ and management forecast activity.

3. Variable Measurement and Research Design

3.1 Variable Measurement

To measure management forecast activity, I utilize three different proxies. The first, *OCCUR*, is an indicator variable equaling one for any firm-year in which management issues a forecast of future annual earnings.[16] The second, *FREQ*, measures the number of annual earnings forecasts (of any horizon) issued by management during the fiscal year. My final measure, *HORIZON*, reflects the number of days between the first management earnings forecast and announcement of year *t*'s earnings.[17,18]

Since I am primarily interested in measuring the degree of estimation error in earnings, I use the modified Dechow-Dichev model of accruals quality as my proxy for EQ (Dechow and Dichev 2002;

[16] I provide detailed descriptions of all variables, including data sources, in Appendix 1.
[17] *HORIZON* is undefined for firms not issuing forecast. I discuss treatment of these observations in Section 3.2.
[18] In addition to *FREQ*, I also employed a specificity-weighted measure of frequency, *MFS*, as in Francis et al. (2008) in untabulated analyses. Specifically, point (closed-range, open-range, qualitative) forecasts are assigned a weight of 4 (3, 2, 1). *MFS* the sum of these scores each year. Results using *MFS* are very similar to *FREQ*, so for brevity I only report results related to *FREQ*.

McNichols 2002).[19] I decompose total accruals quality (*AQ*) into innate (*IAQ*) and discretionary (*DAQ*) components as in Francis et al. (2004; 2005). *AQ* (*IAQ, DAQ*) proxies for total (innate, discretionary) EQ. I modify this procedure to minimize negative correlation between *IAQ* and *DAQ*, which may be driven by measurement error. Specifically, any measurement error in *IAQ* will directly affect *DAQ* (and vice-versa). Since total *AQ* is the sum of *IAQ* and *DAQ* overestimation of one component leads to underestimation of the other. In my setting, this issue is especially troublesome since I predict *IAQ* and *DAQ* have significantly different influences on management forecast activity. If a portion of *DAQ* reflects an inverse measure of *IAQ* and if *IAQ* is positively related to management forecasts (as predicted), then the coefficient estimate on *DAQ* will be biased negatively, the direction of my prediction. Similar logic applies to measurement error in *IAQ*. Diagnostic plots, presented in Appendix 2, reveal significant skewness in the distribution of *DAQ*, which contributes to a significant negative rank correlation between components of *AQ*. To reduce this skewness-induced measurement error, I utilize a Box-Cox (1964) transformation of *AQ*. This procedure essentially eliminates the negative correlation between *IAQ* and *DAQ*. Note that *AQ* and its components are scaled such that greater (more positive) values correspond to higher quality accruals.

To increase the likelihood that my results are attributable to the information quality signal provided by EQ and its components, I include control variables meant to capture information asymmetry and the value relevance of earnings. For information asymmetry, I control for daily return volatility (*RETVOL*), measured as the standard deviation of daily returns over the 12 months ending three months after the end of fiscal year *t-1*, and the average bid-ask spread (*SPREAD*) scaled by the midpoint of the spread over that same period (Welker 1995; Coller and Yohn 1997). For the value relevance of earnings, I include the returns-earnings correlation (*CORR*) over years *t-5* to *t-1* (Lang and Lundholm 1993;

[19] For brevity, I only briefly describe my procedure for measuring EQ in the main text. I fully describe this procedure, including estimation results, in Appendix 2.

Lennox and Park 2006).[20] I utilize market-adjusted returns compounded over the 12 months ending three months after fiscal year-end and earnings before extraordinary items, scaled by beginning of period market value of equity, to compute the correlation.

3.2 Research Design

To test my hypotheses, I estimate the following equation using a probit (OLS, Tobit) regression, where *DV* equals *OCCUR* (*FREQ*, *HORIZON*).[21]

$$DV = \beta_0 + [\ (\beta_1 * AQ_{it-1})\ or\ (\beta_2 * IAQ_{it-1} + \beta_3 * DAQ_{it-1})] + (\beta_4 * RETVOL_{it-1} + \beta_5 * SPREAD_{it-1} + \beta_6 * CORR_{it-1} +)\ \ \Sigma\, \gamma_k * Controls_{it} + \epsilon_{it} \quad (1)$$

Firm (year) subscripts are denoted *i* (*t*). H1a (H1b) predicts β_1 will be significantly positive (negative). H2 predicts that β_2 will be significantly positive, and H3 predicts that β_3 will be significantly negative.[22] Note that I estimate equation (1) both with and without the three EQ controls (*RETVOL*, *SPREAD*, and *CORR*). Higher values of *SPREAD* imply greater adverse selection risk (Welker 1995), implying greater information asymmetry. Therefore, I expect a positive relation between *SPREAD* and management forecast activity (Coller and Yohn 1997). Similarly, higher values of *RETVOL* potentially indicate increased levels of informed trading (French and Roll 1986), suggesting *RETVOL* and disclosure should be positively related. However, prior theoretical and empirical research also provides rationale and support for a negative relation.[23] Thus, I make no prediction as to the sign of *RETVOL*. Finally, since

[20] I elect to use *CORR* instead of a short-window earnings response coefficient (ERC), as in Lennox and Park (2006), to measure value relevance to avoid losing a large percentage of my sample. Computation of ERCs requires a long time-series of analyst coverage, which reduces my sample by over 20%.

[21] For firms that do not issue a management forecast in a given period, *HORIZON* is undefined. However, the information content of the unmade forecast is eventually made public through earnings release. Therefore, from the standpoint of management forecasting activity, I view this as a censored distribution, where the unobserved values for *HORIZON* correspond to those firms not issuing forecasts. Therefore, I use a Tobit model when using *HORIZON* to retain the information in the "withheld" forecasts.

[22] Note that using *DAQ* to test the association between discretionary EQ and each measure of management forecast activity is less econometrically efficient than including *AQ* and determinants of innate EQ as independent variables in equation (3). However, the more efficient approach prevents direct testing of H2 since *IAQ* is replaced by several covariates.

[23] Higher return volatility may decrease the likelihood of disclosure because of managers' aversion to uncertain response (Nagar 1999) or less voluntary disclosure may lead to greater return volatility. Empirical evidence on the relation *RETVOL* disclosure is mixed. For instance, Lang and Lundholm (1993) find some support for a positive relation between return volatility and disclosure quality in their final specification, though they also suggest return volatility and disclosure may be negatively related in other tests.

forecasts are likely more valuable for firms with stronger returns-earnings correlations, I expect *CORR* to be positively related with forecast activity (Lennox and Park 2006).

Remaining control variables are based on prior research and include:

MVE = the natural log of the market value of equity at the beginning of the fiscal period. I expect *MVE* to be positive, as prior research generally suggests a positive relation between firm size and management forecast activity (e.g., Kasznik and Lev 1995; Ajinkya et al. 2005; Baik et al. 2011);

BIGN = an indicator variable equal to one if the firm is audited by one of the Big 6 (5, or 4) auditors. Lang and Lundholm (1993) suggest audit quality is positively related to disclosure quality;

NUMEST = the number of analysts issuing forecasts in the final First Call report prior to fiscal year-end. Prior research generally suggests that analyst following and disclosure are positively related (e.g., Lang and Lundholm 1993; Ajinkya et al. 2005; Baik et al. 2011);

ADISP = the standard deviation of analyst forecasts reported in First Call closest, but prior to fiscal year-end. Analyst uncertainty about earnings likely reflects both market uncertainty about earnings and litigation risk (Ajinkya et al. 2005);

LIT = an indicator variable equal to one for firms in industries with high litigation risk. See Appendix 1 for a list of these industries. Prior research provides mixed support on the relation between litigation risk and voluntary disclosure (Field et al. 2005; Rogers and Van Buskirk 2009);

MKBK = the ratio of the market value of equity to the book value of common equity as of the beginning of the fiscal year. Ajinkya et al. (2005) and Bamber and Cheon (1998) use *MKBK* as a proxy for proprietary costs;

LOSS = an indicator variable equal to one for firms reporting negative earnings. Prior research suggests demands for and properties of disclosures vary for loss firms (Hayn 1995; Ajinkya et al. 2005; Kothari et al. 2009);

NEWS = an indicator equal to 1 for firms with a positive earnings change from year *t-1* to *t*. Prior research suggests good news firms are less likely to issue forecasts, possibly due to litigation risk considerations (Baginski et al. 2002; Ajinkya et al. 2005);

BETA = firm beta obtained from market model estimated using daily returns and the CRSP value-weighted index over the fiscal year. *BETA* proxies for market risk, which relates to various aspects of a firm's information environment (Ajinkya et al. 2005);

INSTOWN = the percentage of firm shares owned by institutions, measured as of the last Thomson Reuters report available prior to fiscal year-end. Ajinkya et al. (2005) use institutional ownership as a proxy for governance and predict that firms with higher governance issue more frequent and accurate forecasts;

FD = an indicator variable equal to 1 for fiscal years occurring after the enactment of Regulation Fair-Disclosure ("Reg FD") on October 23, 2000. Prior research

suggests forecasts of earnings increased following Reg FD (Heflin et al. 2003; Ajinkya et al. 2005).

In addition to these controls, I include fixed effects for year and industry (Fama-French 48 industry classification) in all models.

Note that I exclude earnings volatility, a common control in the management forecast literature, from my empirical models for three related reasons. First, earnings volatility is an alternative measure of earnings quality. Therefore, any significant coefficient on earnings volatility could be interpreted as a second hypothesis test. Second, two determinants of innate EQ, cash flow volatility and sales volatility, correlate highly with earnings volatility. Finally, prior research provides mixed evidence on the relation between earnings volatility and management forecast activity, suggesting its role in forecast activity is unclear. For instance, Ajinkya et al. (2005) and Feng et al. (2009) find no relation between earnings volatility and forecast occurrence, though Ajinkya et al. (2005) and Ball et al. (2012) do find a significantly negative association between earnings volatility and forecast frequency. Further, Ball et al. (2012) fail to find a relation between earnings volatility and horizon.

To test my remaining hypotheses, I introduce interaction terms to equation (1), which allows the effect of *IAQ* and *DAQ* to vary with the level of institutional ownership (H4) and the degree of external verification (H5). To measure external verification, I follow Ball et al. (2012) and use abnormal audit fees (*ABFEES*), defined as the residual from an audit fee expectations model.[24] I then define two indicator variables, *DINSTOWN* and *DABFEES*, equaling one for observations above the annual median of *INSTOWN* and *ABFEES*, respectively.

[24] Specifically, I estimate the following audit fee model each year using all firms in Audit Analytics with sufficient data (firm and year subscripts denoted *i* and *t*, respectively):

$$AUDFEES_{it} = \beta_{0,t} + \beta_{1,t}LN\_ASSETS_{it} + \beta_{2,t}ROA_{it} + \beta_{3,t}ACCR_{it} + \beta_{4,t}CURRENT_{it} + \beta_{5,t}FOREIGN_{it} + \beta_{6,t}SEG_{it} + \beta_{7,t}LIAB_{it} + \beta_{8,t}LOSS_{it} + \beta_{9,t}DEC_{it} + \beta_{10,t}LAG_{it} + \epsilon_{it}$$

where *AUDFEES* is the natural log of audit fees *LN_ASSETS* is the natural log of the firm's assets, *ROA* is net income divided by assets, *ACCR* is the absolute value of total accruals, defined as earnings less operating cash flows, divided by assets, *CURRENT* is current assets (inventory, accounts receivable, and cash) divided by total assets, *FOREIGN* is the ratio of foreign sales to total sales, *SEG* is the number of business segments, *LIAB* is total liabilities scaled by assets, *LOSS* equals one (zero) if the firm reports negative (non-negative) income for the year, *DEC* equals one (zero) if the firm has a December (non-December) fiscal year end, and *LAG* is the number of days between fiscal year end and earnings announcement date. All continuous, unlogged variables are winsorized at the first and 99th percentiles each year.

To test H4, I estimate the following model, where all variables are previously defined, and control variables are the same as in equation (1):

$$DV_{it} = \beta_0 + \beta_1 * IAQ_{it-1} + \beta_2 * IAQ_{it-1} * DINSTOWN_{it} + \beta_3 * DAQ_{it-1} + \beta_4 * DAQ_{it-1} * DINSTOWN_{it} + \beta_5 * DINSTOWN_{it} + \beta_6 * RETVOL_{it-1} + \beta_7 * SPREAD_{it-1} + \beta_8 * CORR_{it-1} + \Sigma\, \gamma_k * Controls_{it} + \epsilon_{it} \quad (2)$$

H4 predicts that β_2 is significantly positive. I make no prediction about the sign or significance of β_4.

To test H5, I estimate the following model, where all variables are previously defined, and control variables are again the same as in equation (1):

$$DV_{it} = \beta_0 + \beta_1 * IAQ_{it-1} + \beta_2 * IAQ_{it-1} * DABFEES_{it} + \beta_3 * DAQ_{it-1} + \beta_4 * DAQ_{it-1} * DABFEES_{it} + \beta_5 * DABFEES_{it} + \beta_6 * RETVOL_{it} + \beta_7 * SPREAD_{it} + \beta_8 * CORR_{it} + \Sigma\, \gamma_k * Controls_{it} + \epsilon_{it} \quad (3)$$

H5 predicts that β_2 is significantly positive, and I make no prediction of the sign or significance of β_4.

4. Sample and Results

4.1 Sample Information

To construct my sample, I obtain required financial statement information from Compustat for firms issuing annual financial statements for fiscal periods ending between 1996 and 2010.[25] I drop firms coded as financial services (SIC 6000-6999) or utilities (SIC 4800-4999) since earnings properties differ for those firms. I obtain returns data from CRSP monthly and daily files as appropriate and institutional ownership data to compute *INSTHOLD* from Thomson Reuters. To compute analyst forecast related variables (*NUMEST, ADISP*), I use the First Call Summary Statistics file, which provides a monthly summary of analyst forecast data and actual reported earnings per share (EPS). I use First Call rather than IBES to reduce the likelihood I incorrectly classify a firm as a non-forecaster. In other words, appearing in First Call's Summary Statistics file ensures that any firm I classify as a non-forecaster is indeed covered by First Call.

For management forecast variables, I collect forecasts of annual earnings issued during the fiscal year from First Call's Company Issued Guidance Detail file. Note that I exclude earnings

[25] Like prior research, I start my sample in 1996 due the change in the legal environment attributable to the passage of the Private Securities and Litigation Reform Act of 1995 (e.g., Gong et al. 2009). The final year of my sample, 2010, is the last year of coverage in First Call's CIG database.

"preannouncements," defined as forecasts issued between fiscal year end and earnings announcement date. These data requirements leave me with a total sample of 9,990 firm-years comprised of 1,606 unique firms.[26]

< INSERT TABLE 1 HERE>

Table 1 presents descriptive statistics for my sample. Consistent with prior research, I winsorize unlogged continuous variables at the first and 99th percentiles to minimize the influence of outliers on estimation. The mean value of *OCCUR* reveals that slightly less than half of my sample corresponds to years in which the firm issues at least one forecast of future earnings. The mean (median) value of 3.89 (4.00) of *FREQ* suggests forecasting firms issue approximately four forecasts per year, consistent with quarterly updates of annual earnings forecasts.[27] Finally, the median (364) and 75th percentile (366) of *HORIZON* suggest a large percentage of firms issue their first forecast approximately one year in advance. The mean value of 316 for *HORIZON* implies the distribution is skewed towards shorter horizons.

Given the scale of accruals quality reveals little, descriptive statistics for *AQ*, *IAQ*, and *DAQ* are relatively uninformative, though I highlight a few characteristics. First, as mentioned earlier, I multiply *AQ*, *IAQ*, and *DAQ* by negative one so that each measure is increasing in quality.[28] Second, the Box-Cox transformation alters the typical scale of these variables. Normally, means are substantially less than 1, as accruals quality equals the standard deviation of asset-scaled accruals. The transformation increases the mean substantially (4.484 for *AQ*), but the relative scale remains similar across the measures.[29] Third, the descriptive statistics suggest that the vast majority of *AQ* arises from *IAQ* and that *DAQ* plays only a minimal role. This interpretation stems from the fact that the intercept of the decomposition model, which reflects yearly but not cross-sectional variation in accruals quality, is included in *IAQ*. In fact,

[26] Additional data requirements required to estimate audit fees yields a smaller sample size in tests of H5.
[27] For *FREQ* and *HORIZON*, I report descriptive statistics for observations where *OCCUR* equals one.
[28] Results presented in Appendix 2 relate to *AQ*, *IAQ*, and *DAQ* before this adjustment.
[29] The uniformly positive values for *AQ* and *IAQ* may appear surprising. However, the relatively small scales of λ, the Box-Cox transformation parameter, and *AQ* (generally on the order of 0.01) yield uniformly negative values, which, after being multiplied by negative one, are uniformly positive.

cross-sectional variation in total *AQ* is split roughly evenly between the two components as evidenced in standard deviations, interquartile ranges, and the adjusted R^2 reported in Table 8 (43.3%), suggesting both innate firm characteristics and managerial discretion play equally significant roles in overall EQ.

Remaining descriptive statistics generally conform to prior research. For instance, I report a mean (median) returns-earnings correlation of 28.1% (38%) which, despite a significant difference in sample period, is similar to the 32% (36%) reported by Lang and Lundholm (1993). The mean (median) values for *SPREAD* and *RETVOL* of 0.008 (0.004) and 0.029 (0.026) are similar to the 0.005 (0.004) and 0.018 (0.0.017) reported in Heflin et al. (2005). Only 9.8% of firms in my sample report negative earnings (*LOSS*=1), which compares favorably to the 12.3% reported by Ajinkya et al. (2005) and 14.7% in Baik et al. (2011). Similarly, Ajinkya et al. (2005) reports mean values of 0.478, 0.307, and 4.202 for *NEWS*, *LIT*, and *MKBK*, whereas I report similar values of 0.655, 0.358, and 3.298. Differences in *NEWS* and *MKBK* can possibly be attributed to the fact that I require six consecutive years of data for my computation of *AQ* (and its components), resulting in a sample with more profitable, less risky firms. Finally, I report a mean (median) of 1.031 (0.977) for *BETA*, which is similar to the 1.047 (0.913) reported by Ajinkya et al. (2005) and 0.965 (0.863) reported by Baik et al. (2011). In summary, my sample data appears quite similar to that used in prior research examining management forecast activity.

< INSERT TABLE 2 HERE>

Table 2 presents select correlations among variables of interest. A few associations warrant attention. First, all three forecast-based proxies for voluntary disclosure are, not surprisingly, significantly positively correlated. Pearson correlations range from 0.468 between *HORIZON* and *FREQ* to 0.733 between *FREQ* and *OCCUR*. While there is common variance explained by the proxies, there are also significant differences suggesting each captures a different aspect of disclosure activity. *AQ* is positively correlated with all three measures of management forecast activity, suggesting that total earnings quality may complement disclosure in the form of forecasts. As predicted in H2, *IAQ* is positively correlated with all three measures of management forecast activity, with Pearson correlations

ranging from 0.202 to 0.340. *DAQ*, on the other hand, is not significantly correlated with any measure of disclosure. Thus, bivariate correlations provide some support for H1a and H2, but no support for H3.

Turning to other correlations, firms with higher *AQ* and *IAQ* experience lower return volatility and bid-ask spreads. Interestingly, *CORR* exhibits relatively little correlation with either *AQ* or its components. In untabulated analysis, I find that intertemporal trends in *AQ, IAQ, DAQ,* and *CORR* contribute to this bivariate relation. Regressing *CORR* on *IAQ* and year fixed effects yields the expected positive relation ($p<0.001$).[30] Interestingly, replacing *IAQ* with *DAQ* yields a negative relation, though of smaller magnitude and significance ($p=0.02$). Turning to other correlations, *RETVOL* and *SPREAD* exhibit significantly negative correlations with all three measures of management forecast activity. This relation likely reflects the impact of forecasts on these variables, meaning firms withholding earnings forecasts experience higher values of *SPREAD* and *RETVOL*. The correlation between *CORR* and *OCCUR* is positive, though low in magnitude, and *CORR* is not significantly correlated with the other two measures of management forecast activity. *INSTOWN* generally relates to all variables as expected—firms with higher institutional ownership have better earnings quality (all three measures), more management forecasts, and lower return volatility and bid-ask spreads. *CORR* is unrelated to *INSTOWN*. *ABFEES* relates positively to management forecast activity, consistent with Ball et al. (2012), though negatively with two of the three measures of EQ. The latter result likely implies that firms with poorer EQ pay more in audit fees.

4.2 Results for H1, H2, and H3

Table 3 presents tests of Hypotheses 1 (a & b), 2, and 3 using forecast occurrence (*OCCUR*) as my measure of management forecast activity. Results are based on probit estimation, and t-statistics are computed using robust standard errors clustered by firm. Column 1 presents results without any of my variables of interest or EQ controls to verify I observe similar inferences as prior research. Results are generally similar to Ajinkya et al. (2005). I find positive and significant coefficients on *INSTHOLD*,

[30] I find similar results using *TREND*, defined as year minus 1994, instead of fixed effects.

MVE, and *FD* (p<0.01, p<0.01, and p<0.05, respectively).[31] I also find negative and significant coefficients on *MKBK*, *LOSS*, *BETA*, and *ADISP* (p<0.01), also consistent with Ajinkya et al. (2005) and in some cases more significant. Inconsistent with Ajinkya et al. (2005), I find a significantly negative coefficient on *LIT*, suggesting firms in high litigation risk industries are less likely to issue earnings guidance. One possible explanation for this difference is that I include industry fixed effects, which allows industry-specific differences in forecast occurrence. I also fail to find a significant auditor effect (p>0.20), possibly due to the fact that my sample has very few firms not audited by Big-4 auditors. Despite these differences, overall control variable coefficient inferences generally agree with prior research

<INSERT TABLE 3 HERE>

Column 2 (3) presents results for tests of H1a and H1b, excluding (including) the EQ controls. Absent EQ controls, I fail to find significant support for either a complementary or substitutive relation between *AQ* and forecast occurrence ($\beta_1=-0.037$, $p>0.10$). In column 3, I introduce the three EQ controls. I find that uncertainty (*RETVOL*) relates negatively to the likelihood of a management forecast ($\beta_4 = -12.457$, $p<0.01$) and the returns-earnings correlation is positively associated with forecast occurrence ($\beta_6 = 0.136$, $p<0.01$). Including the EQ controls leads to weak evidence of a substitutive relation between *AQ* and the likelihood of issuing a forecast ($\beta_1=-0.057$, $p=0.09$), providing some support for H1b.

Columns 4 and 5 present results using accruals quality decomposed into innate and discretionary components. Recall that H2 (H3) predicts that *IAQ* (*DAQ*) complements (substitutes for) management forecast activity. Absent EQ controls, I find strong support for both H2 and H3. Namely, innate EQ is positively associated with the likelihood of issuing a forecast ($\beta_2=0.289$, $p<0.01$), and discretionary EQ is negatively associated with forecast occurrence ($\beta_3= -0.067$, $p<0.03$). However, these two results could be attributable to information asymmetry and/or the value relevance of earnings. Column 5 introduces the

[31] I report one-sided p-values when directional predictions are made.

EQ controls, and I continue to find support for both H2 and H3, though the significance of the complementary relation between *IAQ* and forecast occurrence weakens slightly ($\beta_2 = .172$, $p<0.05$), suggesting the value relevance of earnings and information asymmetry likely played some role in the column (4) results. On the other hand, the significance of the substitutive relation increases ($\beta_3 = -0.076$, $p<0.01$) after introducing the EQ controls.

The remaining four columns in Table 3 repeat analyses presented in columns (2) through (5), replacing *AQ*, *IAQ*¸ and *DAQ* with fractional ranks of each variable. Specifically, to minimize the effects of measurement error, I decile-rank *AQ*, *IAQ*, and *DAQ* each year and then scale these ranks between 0 and 1. In general, conclusions are unaffected when using decile-ranks. For brevity, I focus on columns including EQ controls (columns 7 and 9). I again find weak evidence supporting H1b ($\beta_1 = -0.118$, $p<0.09$). I also find support for H2 and H3, granted the statistical significance of those results declines slightly ($\beta_2 = 0.160$, $p<0.06$; $\beta_3 = -0.121$, $p=0.03$).

<INSERT TABLE 4 HERE>

Table 4 presents tests of H1(a & b), H2, and H3 using management forecast frequency as my measure of disclosure. Reported t-statistics are again based on robust standard errors clustered by firm. Coefficients on control variables are generally consistent with those reported in Table 3, so for brevity I focus on my variables of interest and EQ controls. Columns 2 and 3 report tests of H1a and H1b, excluding and including EQ controls, respectively. As shown, I find no support for either H1a or H1b, irrespective of whether I include the EQ controls. Columns 6 and 7 report similar results using fractional ranks. Thus, the weakly substitutive relation between *AQ* and forecast occurrence does not extend to forecast frequency.

Column 4 of Table 4 reports tests of H2 and H3. Consistent with predictions, I find a significantly positive relation between *IAQ* and forecast frequency ($\beta_2 = 0.918$, $p<0.01$), mirroring results in Table 3. Also similar to Table 3 and consistent with H3, I find a significantly negative relation between *DAQ* and forecast frequency ($\beta_1 = -0.128$, $p=0.03$). Both of these results are robust to the

inclusion of EQ controls, presented in column 5 ($\beta_2 = 0.806, p<0.01; \beta_3 = -0.133, p=0.03$). Note that *RETVOL* again loads negatively, consistent with fewer forecasts in uncertain information environments ($\beta_4 = -9.352, p<0.01$). *SPREAD* now loads positively ($\beta_5 = 7.266, p=0.04$), consistent with expectations. The coefficient on *CORR* is positive, though only weakly significant ($\beta_6 = 0.093, p=0.10$). Finally, columns 8 and 9 report results analogous to columns 4 and 5, replacing continuous values of *IAQ* and *DAQ* with their fractional ranks. Generally, results are consistent with those using continuous measures, though support for H3 weakens both with ($\beta_3 = -0.188, p=0.06$) and without ($\beta_3 = -0.182, p=0.07$) EQ controls.

<INSERT TABLE 5 HERE>

Table 5 presents my final tests of H1 (a & b), H2, and H3 using forecast horizon as a proxy for management's forecast activity. Note that for estimation purposes, I divide *HORIZON* by 365 for expositional convenience. Recall that I use Tobit estimation, treating forecast horizon as a censored distribution since the "news" communicated by forecasting firms is eventually released via preannouncement or earnings announcement after the fiscal year end. I again report t-statistics based on robust standard errors clustered by firm to minimize the effect of serial correlation in residuals. For brevity, I limit my discussion to the effects of *AQ*, *IAQ*, *DAQ*, and the EQ controls.

Columns 2 and 3 of Table 5 report results using *AQ* without and with EQ controls, respectively. In both cases, I fail to find support for H1a or H1b. I find a similar lack of significance when using fractional ranks (columns 6 and 7). Thus, the information quality signal provided by total EQ does not appear to play a role in forecast horizon. Turning to column 4, I once again find support for both H2 and H3. Namely, *IAQ* is associated with longer forecast horizons ($\beta_2 = 0.201, p<0.01$), and *DAQ* relates negatively to forecast horizon ($\beta_3=-0.039, p=0.06$). Both of these results are robust when including EQ controls ($\beta_2=0.132, p=0.02; \beta_3=-0.045, p=0.02$) or using fractional ranks (with EQ controls: $\beta_2=0.126, p=0.02, \beta_3=-0.071, p=0.04$).

In summary, I find consistent evidence that innate (discretionary) EQ complements (substitutes) for voluntary disclosure in the form of management forecast occurrence, frequency, and horizon, supporting H2 and H3. Further, these results appear to be attributable to the information quality signals provided by innate and discretionary EQ, as they remain even after controlling for the value relevance of earnings and information asymmetry. These results suggest that variation in innate and discretionary EQ alters the nature of managers' forecasting decisions in a manner consistent with voluntary disclosure theory.

4.3 Results for H4

I next examine the role institutional ownership in the complementary relation between innate EQ and management forecast activity. Table 6 presents tests of H4. For brevity, I omit coefficient estimates for control variables, though signs and significance are generally similar to those reported in Tables 3, 4, and 5. The term of interest in Table 6 is the interaction *DINSTOWN*IAQ*. H4 predicts a significantly positive coefficient on this interaction.

<INSERT TABLE 6 HERE>

The first (second, third) pair of columns report results using *OCCUR* (*FREQ, HORIZON*) as my measure of management forecast activity. The odd-numbered columns present the models estimated with *DINSTOWN*, while the even numbered columns include *DINSTOWN* and its interaction with *IAQ* and *DAQ*. As shown, *DINSTOWN* is insignificantly different from zero in all three columns (p>0.10). This result likely reflects the fact that I also include a continuous measure of institutional ownership (*INSTOWN*), which continues to load significantly positive in all specifications (untabulated).[32] Turning to column 2, I find that, as predicted, a high level of institutional ownership results in a significantly greater complementary relation between *IAQ* and the likelihood of a management forecast ($\beta_2=0.130$, $p=0.03$). Columns (4) and (6) report similar results; increased levels of institutional ownership result in a

[32] If I exclude *INSTOWN*, I find a significantly positive main effect of *DINSTOWN* in all three specifications. Inferences drawn from interaction terms, discussed below, are generally unchanged.

significantly greater complementary association between innate EQ and forecast frequency ($\beta_2=0.248$, $p=0.04$) and horizon ($\beta_2=0.013$, $p=0.01$). Thus, institutional ownership appears to increase the demand for revelation of high quality information, signaled by innate EQ, which is consistent with H4.

In sum, I find consistent support for H4, suggesting the investor demand for forecast occurrence, frequency, and timeliness (*HORIZON*) is greater when firms have high innate EQ and greater levels of institutional ownership.[33]

4.4 Results for H5

My final analysis builds on results of Ball et al. (2012), who find that managers forecast more frequently and accurately when they commit more resources (audit fees) to external verification of financial statements, presumably because the forecasted information is more reliable. H5 predicts that the complementary relation between innate EQ and management forecast activity is exacerbated when managers commit to more external verification since auditors ostensibly further enhance high quality information.

<INSERT TABLE 7 HERE>

Table 7 presents tests of this hypothesis. As in Table 6, I omit all controls variables (including EQ controls) for expositional convenience. The odd-numbered columns again report results without interaction terms to confirm the main effect of *DABFEES*, while the even-numbered columns introduce interactions between *DABFEES* and EQ components (*IAQ* and *DAQ*). Results in columns 1, 3, and 5 are consistent with Ball et al. (2012); firms committing to higher levels of abnormal audit fees more likely issue forecasts ($\beta_5=0.085$, $p=0.04$), issue forecasts at a greater frequency ($\beta_5=0.195$, $p=0.02$), and issue forecast over longer horizons ($\beta_5=0.009$, $p=0.02$).

The even-numbered columns report tests of H5. Using forecast occurrence (column 2) or horizon (column 4), I fail to find support for H5 ($p>0.10$). However, when using forecast frequency as my

[33] In untabulated analysis, I also test H4 using fractional ranks of *IAQ* and *DAQ*. I find similar results, though significance declines slightly.

measure of management forecast activity, I find significant support for H5 ($\beta_2=0.300$, $p=0.03$), meaning the complementary association between innate EQ and management forecast frequency is even greater when managers commit more resources to external verification. Thus, I find some support for H5, though this result is sensitive to how managers' forecast activity is measured.[34]

5. Conclusion

I investigate the role of the quality of a firm's information, as signaled through innate and discretionary EQ, in management forecast activity. I find that innate EQ relates positively to management forecast occurrence, frequency, and horizon, while discretionary EQ relates negatively. The former result is consistent with theory suggesting firms with high quality information issue more voluntary disclosures (e.g., Dye 1985; Jung and Kwon 1988; Verrecchia 1990). The relation between discretionary EQ and management forecast activity is consistent with theory suggesting that costs of information attainment and disclosure impede revelation of high quality information, leading to a substitutive relation (e.g., Verrecchia 1983; Penno 1997). Further, I find that higher levels of institutional ownership exacerbate the positive relation between innate EQ and all three measures of disclosure, and increased external verification increases the positive relation between innate EQ and forecast frequency.

My results provide the first empirical link between the quality of a firm's information, a frequently modeled disclosure antecedent, and management forecasts, the most widely studied form of voluntary disclosure. Further, I show that ignoring the differential information signals conveyed through innate and discretionary EQ obscures the role of information quality in management forecast choices. My results also illustrate that seemingly conflicting disclosure theories can coexist. Finally, I add to the long line of research examining determinants of management forecast decisions and, more broadly, voluntary disclosure choices.

My study also provides several avenues for future research. For example, Francis et al. (2008) conclude that EQ, not disclosure quality, has a first order effect on a firm's cost of equity capital. Prior

[34] In untabulated analyses, I find qualitatively identical results using fractional ranks of *IAQ* and *DAQ*.

management forecast research suggests that forecasts (or properties of forecasts) affect capital market outcomes, including bid-ask spreads, analyst forecasts, stock prices, and the cost of equity (Baginski and Hassell 1990; Pownall et al. 1993; Baginski et al. 1993; Coller and Yohn 1997; Hirst et al. 2008; Baginski and Rakow 2012; Li and Zhuang 2012). Innate and discretionary EQ likely relate to many of these same market outcomes, raising the potential for a correlated omitted variables problem as described in Francis et al. (2008). Further, Hirst et al. (2008) observe that extant research generally fails to consider interactive effects of disclosure antecedents (i.e., information quality) and forecast activity on outcomes (i.e., reduced information asymmetry). The management forecast-driven reduction in bid-ask spread documented in Coller and Yohn (1997) potentially varies with the quality of the information underlying the forecasts. Similarly, market reactions and analyst forecast revisions in response to management forecasts may be moderated by the quality of the underlying information. My study provides a framework for examining these important questions.

Appendix 1 – Variable Definitions

(Compustat data items in ***BOLD*****)**

OCCUR	Indicator variable equaling one for any fiscal year in First Call where firm reports a forecast of annual earnings, excluding pre-announcements (defined as forecast of fiscal year *t* earnings issued between end of fiscal year *t* and earnings announcement date).
FREQ	The number non-preannouncement annual earnings forecasts reported in First Call in fiscal year *t*.
HORIZON	The number of days between the first forecast of fiscal year *t* earnings and earnings announcement.
AQ	Earnings quality, estimated as standard deviation of firm-residuals over years t-5 to t-1 from cross-sectional Dechow-Dichev accruals quality models estimated by year and industry (Dechow and Dichev 2002; McNichols 2002), transformed using maximum likelihood estimations of the Box-Cox (1964) family of power transformations. See Appendix 2 for more detail.
IAQ	Innate accruals quality, which proxies for innate EQ. Predicted value from equation (A2) estimated using transformed version of *AQ*. See Appendix 2 for more detail.
DAQ	Discretionary accruals quality, which proxies for discretionary EQ. Residual from equation (A2) estimated using transformed version of *AQ*. See Appendix 2 for more detail.
SPREAD	The average daily bid-ask spread, scaled by the midpoint of the spread, over the 12 months ending three months following the end of fiscal year t-1.
RETVOL	The standard deviation of daily returns over the 12 months ending three months following the end of fiscal year t-1.
CORR	The correlation between annual earnings (**IB**), scaled by beginning of period market value of equity, and annual market-adjusted returns from year *t-5* to *t-1*. I use the CRSP value-weighted return index to market-adjust firm-specific returns. Annual returns are compounded over the 12 months ending three months following the end of each fiscal year.
MVE	The natural log of the market value of equity, defined as **CSHO** times **PRCC_F**, at the beginning of fiscal year t
BIGN	An indicator variable equal to one for any observation where **AU** is between 0 and 8 (Big-N Auditors).
NUMEST	The number of analysts issuing an earnings forecast in the First Call

	Summary report issued closest to the observation's fiscal year end.
ADISP	The standard deviation of earnings forecasts issued by analysts reported by First Call in the report issued closest to the observation's fiscal year end.
LIT	An indicator equaling 1 for high litigation risk industries, defined as **SIC** between 2833 and 2836, 8731 and 8734, 3570 and 3577, 7370 and 7374, 3600 and 3674, and 5200 and 5961.
MKBK	The ratio of the market value of equity (**CSHO** times **PRCC_F**) to the book value of equity (**CEQ**) at the beginning of fiscal year *t*.
LOSS	An indicator variable equaling one in years when actual earnings per share reported by First Call is less than zero.
NEWS	An indicator variable equaling one when current year earnings per share reported in First Call exceeds prior year earnings per share.
BETA	Beta obtained from regressing firm daily returns on CRSP value-weighted market returns over the observation's fiscal year.
INSTOWN	The percentage of stock owned by institutional investors. Computed as shares owned by institutions as reported by Thomson-Reuters on the report date closest to fiscal year end divided by shares outstanding on that date per CRSP.
FD	Indicator variable equaling 1 for fiscal years ending after October 23, 2000.
DINSTOWN	Indicator variable equaling 1 for observations exceeding yearly median value of *INSTOWN*
ABFEES	Abnormal audit fees, defined using audit fee model in Ball et al. (2012). See footnote 24 for more detail.
DABFEES	Indicator variable equaling 1 for observations exceeding yearly median value of *ABFEES*

*Variables Referred to in Appendix 2 (Compustat data items in **BOLD**)*

TCA	Total change in working capital accruals over fiscal year, computed as change in **ACT** minus change in **LCT** minus change in **CHE** plus change in **DLC**, scaled by average **AT** over fiscal period
CFO	Cash flows from operations, computed as **OANCF** scaled by average **AT** over fiscal period
ΔREV	Change in **SALE** from period t-1 to t, scaled by average **AT** over fiscal period

PPE	Gross property plant and equipment (**PPEGT**) scaled by average **AT** over fiscal period
AQ	Accruals quality, defined as the Box-Cox transformed standard deviation of firm-residuals over years t-5 to t-1 from cross-sectional Dechow-Dichev accruals quality models estimated by year and industry.
SIZE	The natural logarithm of **AT** in the fiscal period
CFVOL	The standard deviation of cash flows (**OANCF**) over fiscal years t-5 to t-1, scaled by **AT**
SALEVOL	The standard deviation of sales (**SALE)** over fiscal years t-5 to t-1, scaled by **AT**
OPCYCLE	The natural logarithm of the firm's operating cycle, computed as 360 divided by sales turnover plus 360 divided by inventory turnover. Sales turnover equals **SALE** divided by average **RECTR** over fiscal year; Inventory turnover equals **COGS** divided by average **INVT** over fiscal year.
NEG	The number negative earnings (**IB** less than 0) over years t-5 to t-1.
INT	**XAD** plus **XRD** divided by average **AT**. Missing values for each variable are replaced with zero.
INT_DUM	Indicator variable equaling one for observations where **XAD** or **XRD** equals zero.
CAP	**PPENT** divided by average **AT**.
IAQ	Innate earnings quality, defined as the predicted value from equation (A2) estimated using Box-Cox transformed version of *AQ*.
DAQ	Discretionary earnings quality, defined as the residual from equation (A2) estimated using Box-Cox transformed version of *AQ*.

Appendix 2 – Measuring Earnings Quality

To proxy for EQ, I follow extensive prior research and use the modified Dechow-Dichev measure of accruals quality (Dechow and Dichev 2002; McNichols 2002; Francis et al. 2008). I first estimate the following cross-sectional regression (firm, year, and industry subscripts denoted, *i*, *t*, and *j*, respectively)*:*

$$TCA_{it} = \alpha_{0,j,t} + \alpha_{1,j,t}CFO_{it-1} + \alpha_{2,j,t}CFO_{it} + \alpha_{3,j,t}CFO_{it+1} + \alpha_{4,j,t}\Delta REV_{it} + \alpha_{5,j,t}PPE_{jt} + \tau_{it} \quad \text{(A1)}$$

where *TCA* is total current accruals in year *t*, $CFO_{i,t-1}$ ($CFO_{i,t}$, $CFO_{i,t+1}$) is cash flows from operations in year *t-1* (*t*, *t+1*), *ΔREV* is the change in revenue from year *t-1* to year *t*, and *PPE* is the gross property, plant, and equipment at the end of year *t*.[35] All variables are scaled by average total assets and winsorized at the first and 99th percentiles. I estimate equation (A1) using the full Compustat population for each Fama-French 48 classified industry with at least 20 observations in year *t*. For brevity, I do not report estimation results, but I find results consistent with prior research.[36] *AQ* is defined as the standard deviation of firm residuals from year *t-5* to *t-1*, meaning higher values of *AQ* reflect poorer quality accruals.

To decompose *AQ* into innate accruals quality (*IAQ)* and discretionary accruals quality (*DAQ*), I regress *AQ* on innate firm characteristics identified in Francis et al. (2004). The factors include firm size (*SIZE)*, defined as the natural log of total assets, cash flow volatility (*CFVOL)*, defined as the standard deviation of cash flows scaled by assets, sales volatility (*SALEVOL*), defined as the standard deviation of sales scaled by assets, the natural log of the operating cycle (*OPCYCLE*), the frequency of negative earnings realizations (*NEG*), intangibles assets scaled by total assets (*INT*), and capital assets scaled by total assets (*CAP*).[37] Note that *INT* is measured as the sum of research and development (R&D) and advertising expense, data-items frequently missing in Compustat. Missing values for these variables are set to zero. To account for possible differences between firms reporting and not reporting R&D and/or

[35] Detailed variable definitions can be found in Appendix 1.
[36] I use the full Compustat population for estimating *AQ* as well as *IAQ* and *DAQ* (defined later) to increase the power of each regression model.
[37] I use a 5 year window for variables requiring a time series of values (e.g. *CFVOL*, *SALEVOL*, *NEG*). I do not use a longer window, such as the 10 year horizon in Francis et al. (2008), to avoid imposing additional data requirements on my sample and to be consistent with the horizon used to compute *AQ*.

advertising, I include a dummy variable (*INTDUM*) equaling 1 for those observations with no reported advertising or R&D (Francis et al. 2004). All unlogged continuous variables are winsorized at the first and 99th percentile. The decomposition model is presented in equation (A2) (firm and year subscripts denoted *i* and *t*, respectively):

$$AQ_{i,t} = \beta_{0,t} + \beta_{1,t}SIZE_{i,t} + \beta_{2,t}CFVOL_{i,t} + \beta_{3,t}SALEVOL_{i,t} + \beta_{4,t}OPCYCLE_{i,t} + \beta_{5,t}NEG_{i,t} + \beta_{6,t}INT_{i,t} + \beta_{7,t}INTDUM_{i,t} + \beta_{8,t}CAP_{i,t} + v_{i,t} \quad \text{(A2)}$$

where all variables are defined previously. I discuss estimation results shortly.

I define *IAQ* as the predicted value and *DAQ* as the residual from these yearly regressions. Note that any measurement error in *IAQ* will directly affect *DAQ* (and vice-versa). Since total *AQ* is the sum of *IAQ* and *DAQ* overestimation of one component leads to underestimation of the other. In my setting, this issue is especially troublesome since I predict *IAQ* and *DAQ* have significantly different influences on voluntary disclosure. If a portion of *DAQ* reflects an inverse measure of *IAQ* and if *IAQ* is positively related to voluntary disclosure (as predicted), then the coefficient estimate on *DAQ* will be biased negatively, in the direction of my prediction. Similar logic applies to measurement error in *IAQ*.

Departure from a normal distribution likely contributes to the aforementioned measurement error, as positive (negative) skewness in *DAQ* will lead to negative (positive) skewness in *IAQ*. To assess the extent to which regression residuals (*DAQ*) diverge from the assumed normal distribution, I review a Q-Q plot, presented in Figure 1A. The Q-Q plot maps quantiles of a variable of interest, which in my case is *DAQ*, against quantiles of a standard normal distribution. Data that is normally distributed will follow a linear pattern, while any departures from linearity imply departures from normality. As shown in Figure 1A, the residuals from estimating equation (A2) demonstrate significant departures from normality in both tails, suggesting a higher proportion of residuals fall in outer quantiles than expected in a standard normal distribution. I posit that this situation leads to measurement error induced negative correlation in *DAQ* and *IAQ*. Consistent with this expectation, I find a significant rank correlation of -0.34 (untabulated) between *IAQ* and *DAQ*.

<INSERT FIGURE 1A AND 1B HERE>

Several econometric techniques aid in improving the linear fit of a model, which potentially enhances the normality of residuals. I employ one such method, the Box-Cox transformation, which introduces a parameter, λ, to traditional OLS estimation (Box and Cox 1964). The maximum likelihood estimate (MLE) of λ maximizes the likelihood function of the underlying regression.[38] Assuming *y* denotes the dependent variable in a classical regression model, the family of transformations is expressed as $y^* = y(\lambda)$ where

$$y(\lambda) = \begin{cases} \frac{y^{\lambda}-1}{\lambda} \; for \; \lambda \neq 0 \\ \ln(y) \; for \; \lambda = 0 \end{cases} \tag{A3}$$

The resulting score equations is a set of non-linear, implicit functions, which must be solved using non-linear estimation methods. A λ value of one implies no transformation is necessary.[39]

To implement this procedure, I find the MLE of λ for each year in my sample, which I then use transform the dependent variable (*AQ*) as described in equation (A3).[40] Note that power transformations, including Box-Cox, are monotonic and continuous. Therefore, there is no change in the ranking of total earnings quality. This procedure yields estimates for λ ranging from -0.059 to 0.090 (untabulated), and the mean of the yearly estimates, 0.025, is marginally different from zero (p=0.07).[41] These estimates suggest that the transformations are similar, though not identical, to a natural log transformation. Finally, every single yearly estimate is significantly different from one, suggesting the transformation substantively improves the model's fit.

[38] Box-Cox requires only that the transformed variable be strictly positive, a property *AQ* satisfies since it is a standard deviation.

[39] If one conditions the score equations on a selected value of λ, then traditional OLS may be used to manually find a maximized likelihood function. However, standard errors from this method will be conditional on the value of λ. To obtain unconditional standard errors, or standard errors that account for variance in λ, non-linear estimation methods are required.

[40] The Box-Cox transformation can be applied on any or all of the independent variables in a model as well so long as these variables are strictly positive. For simplicity, I limit transformation to the dependent variable, which, as I show shortly, substantially reduces non-linearity.

[41] In addition to using yearly estimates of λ, I also use a λ derived from the pooled sample as well as the natural log, which corresponds to λ=0. The method discussed in the text (yearly λ estimates) performs best in terms of improving residual behavior and minimizing negative correlation across earnings quality components.

Table 8 presents results from estimating equation (A2) using original (column 1) and transformed (column 2) measures of *AQ*. In both specifications, coefficients of independent variables are generally significant and in the predicted direction. The only differences between the two sets of estimation results relate to intangibles intensity (*INT* and *INTDUM*) and *OPCYCLE*. Namely, compared to column 1, the signs on both *INT* and *INTDUM* reverse and drop to only marginal significance (p=0.11 and p=0.07, respectively) in column 2, suggesting that both higher levels and unreported levels of intangible assets contribute to *better* innate earnings quality. The latter result is consistent with Francis et al. (2004).[42] In addition, the significantly positive (p<0.05) coefficient for *OPCYCLE* suggests that, as expected, longer operating cycles lead to poorer quality earnings. In sum, employing the Box-Cox transformation has little effect on the relation between *AQ* innate earnings quality determinants. In fact, overall model specification improves when using the transformed *AQ*. Relative to the untransformed model, average adjusted R^2 values increase by 14.8% (from 37.7% to 43.3%), suggesting the transformed version of *AQ* fits the data significantly better.

More importantly, however, is the change in normality of *DAQ*. Figure 1B presents a Q-Q plot analogous to that in Figure 1A. While the pattern is not perfectly linear, it follows the one-to-one quantile mapping line much more closely than the plot in Figure 1A, exhibiting only slight deviations at each tail.[43] In perhaps the most telling test of improvement, the rank correlation between the transformed *IAQ* and *DAQ* drops to an insignificant 0.006 (p>0.10), a 98% reduction from the correlation between untransformed *AQ* components. Thus, the Box-Cox transformation appears to strengthen the fit of the model as well as reduce measurement-error induced correlation. Both of these features increase the likelihood I properly extract the component of earnings quality attributable to innate and discretionary firm characteristics, removing doubt that measurement error contributes to my results.

[42] While Francis et al. (2004) report a positive coefficient on intangible asset intensity when using accruals quality as a proxy for earnings quality, they find a negative relation between intangibles and two other measures of earnings quality, persistence and predictability, so the notion that intangible assets are associated with higher quality earnings has some empirical support.

[43] In untabulated analysis, I use the Shapiro-Wilk test to assess the normality of the residuals from both the original and transformed specifications of Equation (2). In both cases, I reject the null hypothesis that the data is normally distributed (p<0.01). Thus, while transformation yields residuals more closely aligned to a normal distribution as shown in Figure 1B, it is not perfect.

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Figure 1A – Q-Q Plot from Decomposition of Untransformed EQ

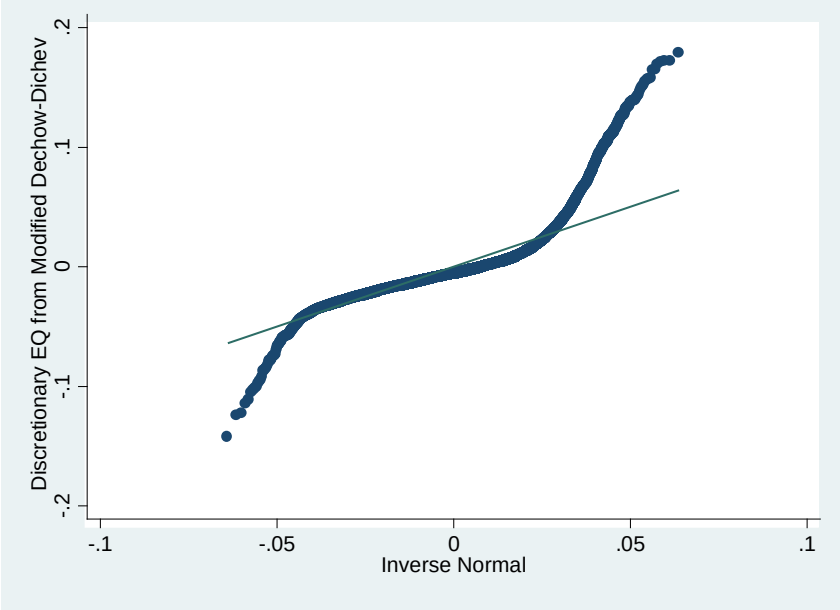

Figure 1B – Q-Q Plot from Decomposition of Transformed EQ

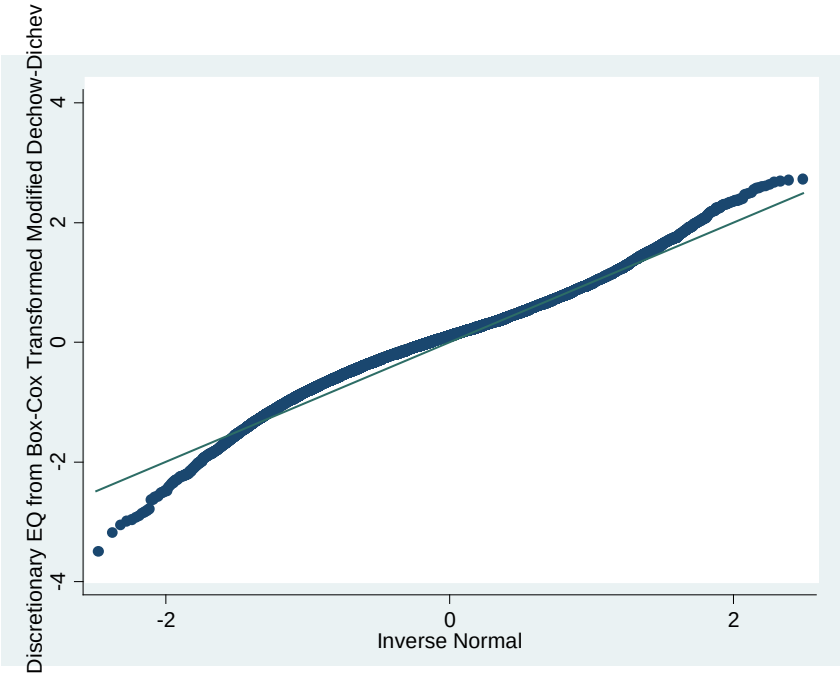

Figure 1A (Figure 1B) presents a Q-Q plot of residuals from the untransformed (Box Cox Transformed) regression of *AQ*, defined as the standard deviation of firm residuals from the modified Dechow-Dichev model of accruals quality (Dechow and Dichev 2002; McNichols 2002), on innate determinants. The Q-Q plot maps quantiles of the standard normal distribution to quantiles of a variable of interest.

Table 1 – Descriptive Statistics

VARIABLE	N	MEAN	STD. DEV.	25%	50%	75%
OCCUR	9,990	0.497	0.500	0.000	0.000	1.000
FREQ	4,967	3.889	2.558	2.000	4.000	5.000
HORIZON	4,967	315.998	90.140	286.000	364.000	366.000
AQ	9,990	4.501	0.817	3.913	4.412	5.010
IAQ	9,990	4.483	0.574	4.030	4.433	4.884
DAQ	9,990	0.018	0.576	-0.350	-0.007	0.349
CORR	9,990	0.281	0.503	-0.080	0.380	0.706
SPREAD	9,990	0.008	0.010	0.001	0.004	0.012
RETVOL	9,990	0.029	0.013	0.019	0.026	0.035
ABFEES	7,738	0.105	0.521	-0.248	0.115	0.456
ADISP	9,990	0.037	0.062	0.010	0.020	0.040
BETA	9,990	1.031	0.525	0.656	0.977	1.336
BIGN	9,990	0.932	0.251	1.000	1.000	1.000
FD	9,990	0.792	0.406	1.000	1.000	1.000
INSTOWN	9,990	0.682	0.247	0.541	0.718	0.854
LIT	9,990	0.358	0.480	0.000	0.000	1.000
LOSS	9,990	0.098	0.298	0.000	0.000	0.000
MKBK	9,990	3.298	3.112	1.612	2.465	3.918
MVE (in millions)	9,990	5,862.262	18,958.660	390.521	1,095.619	3,600.354
MVE	9,990	7.150	1.641	5.967	6.999	8.189
NEWS	9,990	0.655	0.476	0.000	1.000	1.000
NUMEST	9,990	8.220	5.871	4.000	7.000	11.000

Table 1 presents descriptive statistics for the full sample of 9,990 firm-years, comprised of 1,606 unique firms. *OCCUR* is an indicator equaling 1 in any fiscal year in which a firm makes a forecast of any future year's earnings. *FREQ* equals the number of annual earnings forecasts issued during the fiscal year. *HORIZON* is the number of days between the forecast date and earnings announcement date. For *FREQ* and *HORIZON*, I only report descriptive statistics for forecasting firms (i.e. *OCCUR=1*). *AQ* is total accruals quality, transformed using the Box-Cox transformation. *IAQ (DAQ)* is innate (discretionary) accruals quality obtained from decomposing *AQ* using the Francis et al. (2004; 2005) accruals quality decomposition. *AQ, IAQ,* and *DAQ* are scaled such that higher values correspond to higher quality accruals. *CORR* is the correlation between earnings and market-adjusted returns over the 5 year period ending in *t-1*. *SPREAD* is average daily bid-ask spread, scaled by the midpoint, over fiscal year *t-1*. *RETVOL* is the standard deviation of daily returns over fiscal year *t-1*. *ABFEES* refers to abnormal audit fees, estimated based on the Ball et al. (2012) model of expected audit fees. *ADISP* measures analyst forecast dispersion based on the latest earnings forecast issued in the fiscal year. *BETA* comes from regressing daily firm returns on CRSP value-weighted market returns over the fiscal year. *BIGN* is an indicator variable equaling 1 for any observation audited by a Big N auditor. *FD* equals 1 for any observation with fiscal year end after October 23, 2000. *INSTOWN* is the percentage of shares owned by institutions as reported by Thomson-Reuters in the report issued closest, but prior to fiscal year end. *LIT* is an indicator variable equaling 1 for high litigation risk industries (SIC between 2833 and 2836, 8731 and 8734, 3570 and 3577, 7370 and 7374, 3600 and 3674, and 5200 and 5961). *LOSS* equals 1 if the firm reports negative earnings in fiscal year *t*. *MKBK* is the ratio of the market value of equity to the book value of equity. *MVE* is the natural log of the market value of equity. *NEWS* is an indicator equaling 1 if the firm reports an earnings-per-share increase from year *t-1* to year *t*. *NUMEST* is the number of analyst estimates reported in the final First Call summary report prior to the firm's fiscal year end. All continuous, unlogged, variables are winsorized at the first and 99th percentiles.

Table 2 – Select Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) AQ		0.724	0.657	0.145	0.216	0.236	-0.039	-0.298	-0.577	0.315	*-0.021*
(2) IAQ	0.709		*0.005*	0.204	0.301	0.323	*-0.016*	-0.370	-0.760	0.398	*-0.010*
(3) DAQ	0.712	*0.009*		*-0.008*	*-0.007*	*0.007*	-0.041	-0.039	-0.037	0.048	*-0.020*
(4) OCCUR	0.135	0.202	*-0.011*		0.929	*N/A*	0.050	-0.177	-0.198	0.179	0.081
(5) FREQ	0.223	0.329	*-0.011*	0.733		0.508	0.040	-0.215	-0.292	0.223	0.094
(6) HORIZON	0.238	0.340	*0.007*	*N/A*	0.468		*-0.007*	-0.087	-0.314	0.189	0.059
(7) CORR	-0.034	*-0.006*	-0.041	0.053	*0.017*	*-0.015*		*0.012*	0.065	*-0.011*	-0.031
(8) RETVOL	-0.285	-0.365	-0.041	-0.185	-0.205	-0.084	*-0.006*		0.309	-0.123	-0.094
(9) SPREAD	-0.431	-0.566	-0.047	-0.172	-0.246	-0.308	0.041	0.199		-0.469	*-0.011*
(10) INSTOWN	0.283	0.350	0.052	0.181	0.213	0.180	*0.000*	-0.139	-0.396		0.049
(11) ABFEES	-0.032	*-0.016*	-0.028	0.084	0.090	0.075	*-0.022*	-0.083	-0.035	0.061	

Table 2 reports Spearman (Pearson) correlations above (below) diagonal. Italicized correlations are not significantly different from zero (p>0.05). *AQ* is total accruals quality, transformed using the Box-Cox transformation. *IAQ* (*DAQ*) is innate (discretionary) accruals quality obtained from decomposing *AQ* using the Francis et al. (2004; 2005) accruals quality decomposition. *AQ*, *IAQ*, and *DAQ* are scaled such that higher values correspond to higher quality accruals. *OCCUR* is an indicator equaling 1 in any fiscal year in which a firm makes a forecast of any future year's earnings. *FREQ* equals then number of annual earnings forecasts issued during the fiscal year. *HORIZON* is the number of days between the forecast date and earnings announcement date. *CORR* is the correlation between earnings and market-adjusted returns over the 5 year period ending in t-1. *RETVOL* is the standard deviation of daily returns over fiscal year t-1. *SPREAD* is average daily bid-ask spread, scaled by the midpoint, over fiscal year t-1. *INSTOWN* is the percentage of shares owned by institutions as reported by Thomson-Reuters in the report issued closest, but prior to fiscal year end.

Table 3 – Effect of Earnings Quality on Forecast Occurrence

		Continuous					Fractional Ranks			
Variable	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AQ	+ / -		-0.037	-0.057			-0.077	-0.118		
			(-1.10)	(-1.67)			(-1.11)	(-1.70)		
IAQ	+				0.289	0.172			0.271	0.160
					(2.95)	(1.73)			(2.74)	(1.58)
DAQ	-				-0.067	-0.076			-0.105	-0.121
					(-1.89)	(-2.14)			(-1.63)	(-1.87)
CORR	+			0.136		0.126		0.135		0.130
				(3.75)		(3.46)		(3.74)		(3.57)
RETVOL	+ / -			-12.457		-11.484		-12.491		-11.430
				(-5.55)		(-5.06)		(-5.57)		(-5.06)
SPREAD	+ / -			-0.809		-1.617		-0.922		-1.388
				(-0.29)		(-0.58)		(-0.33)		(-0.49)
INSTOWN	+	0.476	0.481	0.414	0.481	0.415	0.481	0.415	0.479	0.415
		(5.09)	(5.13)	(4.32)	(5.11)	(4.32)	(5.14)	(4.33)	(5.09)	(4.31)
MVE	+	0.155	0.160	0.116	0.119	0.089	0.160	0.116	0.122	0.092
		(7.12)	(7.27)	(4.69)	(4.76)	(3.26)	(7.23)	(4.67)	(4.79)	(3.32)
BIGN	+	0.062	0.063	0.071	0.043	0.057	0.063	0.071	0.049	0.061
		(0.73)	(0.75)	(0.83)	(0.51)	(0.67)	(0.75)	(0.83)	(0.58)	(0.72)
LIT	+ / -	-0.229	-0.226	-0.186	-0.211	-0.180	-0.226	-0.187	-0.215	-0.184
		(-2.05)	(-2.03)	(-1.66)	(-1.91)	(-1.61)	(-2.03)	(-1.66)	(-1.95)	(-1.64)
MKBK	+ / -	-0.017	-0.018	-0.016	-0.013	-0.013	-0.018	-0.015	-0.014	-0.013
		(-2.28)	(-2.41)	(-2.11)	(-1.76)	(-1.68)	(-2.40)	(-2.09)	(-1.88)	(-1.75)
LOSS	+ / -	-0.543	-0.547	-0.463	-0.500	-0.436	-0.546	-0.461	-0.516	-0.445
		(-8.73)	(-8.79)	(-7.38)	(-8.14)	(-7.01)	(-8.78)	(-7.36)	(-8.40)	(-7.16)
NEWS	-	0.023	0.023	0.026	0.029	0.031	0.024	0.027	0.028	0.031
		(0.74)	(0.74)	(0.84)	(0.91)	(0.97)	(0.75)	(0.85)	(0.90)	(0.97)

Table 3 (Continued)

Variable	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BETA	+ / -	-0.247	-0.251	-0.135	-0.231	-0.132	-0.251	-0.136	-0.228	-0.130
		(-5.84)	(-5.94)	(-3.07)	(-5.49)	(-3.01)	(-5.94)	(-3.08)	(-5.39)	(-2.95)
ADISP	+ / -	-2.330	-2.344	-2.279	-2.429	-2.341	-2.345	-2.280	-2.398	-2.320
		(-7.14)	(-7.20)	(-7.01)	(-7.47)	(-7.22)	(-7.20)	(-7.01)	(-7.37)	(-7.16)
NUMEST	+	-0.003	-0.004	0.001	-0.003	0.001	-0.004	0.001	-0.003	0.001
		(-0.56)	(-0.63)	(0.13)	(-0.56)	(0.13)	(-0.64)	(0.13)	(-0.57)	(0.12)
FD	+	0.246	0.245	0.227	0.253	0.235	0.245	0.228	0.255	0.237
		(1.71)	(1.71)	(1.59)	(1.77)	(1.64)	(1.71)	(1.59)	(1.78)	(1.65)
Constant	+ / -	-1.457	-1.341	-0.830	-2.362	-1.555	-1.446	-0.985	-1.350	-0.936
		(-3.36)	(-3.01)	(-1.74)	(-4.42)	(-2.77)	(-3.33)	(-2.12)	(-3.03)	(-1.98)
Year and Industry FEs?		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		9,990	9,990	9,990	9,990	9,990	9,990	9,990	9,990	9,990
Wald χ^{-2}		871.4	871.9	875.7	874.6	879.5	871.5	875.2	875.1	879.2
Significance		<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Table 3 reports coefficients (z-statistics) estimating the following probit model:

$$Pr(OCCUR_{it}=1) = \beta_0 + [\,(\beta_1 * EQ_{it}) \text{ or } (\beta_2 * IEQ_{it} + \beta_3 * DEQ_{it})] + \beta_4 * RETVOL_{it} + \beta_5 * SPREAD_{it} + \beta_6 * CORR_{it} + \Sigma\, \gamma_k * Controls + \epsilon_{it}$$

OCCUR is an indicator equaling 1 in any fiscal year in which a firm makes a forecast of any future year's earnings. *AQ* is total accruals quality, transformed using the Box-Cox transformation. *IAQ* (*DAQ*) is innate (discretionary) accruals quality obtained from decomposing *AQ* using the Francis et al. (2004; 2005) accruals quality decomposition. *AQ*, *IAQ*, and *DAQ* are scaled such that higher values correspond to higher quality accruals. *CORR* is the correlation between earnings and market adjusted returns over the 5 year period ending in t-1. *RETVOL* is the standard deviation of daily returns over fiscal year t-1. *SPREAD* is average daily bid-ask spread, scaled by the midpoint, over fiscal year t-1. *INSTOWN* is the percentage of shares owned by institutions as reported by Thomson-Reuters in the report issued closest, but prior to fiscal year end. *MVE* is the natural log of the market value of equity. *BIGN* is an indicator variable equaling 1 for any observation audited by a Big N auditor. *LIT* is an indicator variable equaling 1 for high litigation risk industries (SIC between 2833 and 2836, 8731 and 8734, 3570 and 3577, 7370 and 7374, 3600 and 3674, and 5200 and 5961). *MKBK* is the ratio of the market value of equity to the book value of equity. *LOSS* equals 1 if the firm reports negative earnings in fiscal year *t*. *NEWS* is an indicator equaling 1 if the firm reports an earnings-per-share increase from year *t-1* to year *t*. *BETA* comes from regressing daily firm returns on CRSP value-weighted market returns over the fiscal year. *ADISP* measures analyst forecast dispersion based on the latest earnings forecast issued in the fiscal year. *NUMEST* is the number of analyst estimates reported in the final First Call summary report prior to the firm's fiscal year end. *FD* equals 1 for any observation with fiscal year end after October 23, 2000. All continuous, unlogged, variables are winsorized at the first and 99th percentiles. Z-statistics are based on standard errors clustered at the firm level. Z-statistics greater than 2.58 (1.96, 1.645) in absolute magnitude signify significance at the p<0.01 (p<0.05, p<0.10) level (two-sided).

Table 4 – Effect of Earnings Quality on Forecast Frequency

		Continuous					Fractional Ranks			
Variable	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AQ	+ / -		-0.038	-0.057			-0.122	-0.160		
			(-0.57)	(-0.87)			(-0.95)	(-1.24)		
IAQ	+				0.918	0.806			0.738	0.630
					(4.75)	(4.02)			(4.14)	(3.45)
DAQ	-				-0.128	-0.133			-0.182	-0.188
					(-1.87)	(-1.95)			(-1.49)	(-1.54)
CORR	+			0.131		0.093		0.130		0.111
				(1.84)		(1.28)		(1.83)		(1.54)
RETVOL	+ / -			-12.876		-9.352		-13.135		-9.761
				(-3.65)		(-2.59)		(-3.74)		(-2.76)
SPREAD	+ / -			10.052		7.266		9.930		8.665
				(2.51)		(1.81)		(2.48)		(2.14)
INSTOWN	+	0.691	0.695	0.683	0.699	0.689	0.699	0.685	0.691	0.687
		(3.80)	(3.81)	(3.73)	(3.81)	(3.75)	(3.83)	(3.75)	(3.78)	(3.74)
LNMVE	+	0.315	0.320	0.298	0.199	0.195	0.323	0.300	0.223	0.221
		(7.59)	(7.70)	(6.31)	(4.26)	(3.79)	(7.72)	(6.33)	(4.73)	(4.23)
BIGN	+	0.174	0.175	0.166	0.114	0.113	0.176	0.167	0.138	0.134
		(1.13)	(1.14)	(1.07)	(0.73)	(0.73)	(1.14)	(1.08)	(0.89)	(0.87)
LIT	+ / -	-0.339	-0.337	-0.281	-0.292	-0.256	-0.336	-0.280	-0.306	-0.266
		(-1.59)	(-1.59)	(-1.31)	(-1.39)	(-1.21)	(-1.58)	(-1.30)	(-1.45)	(-1.25)
MKBK	+ / -	-0.024	-0.025	-0.022	-0.011	-0.011	-0.025	-0.022	-0.016	-0.015
		(-1.69)	(-1.76)	(-1.56)	(-0.78)	(-0.73)	(-1.78)	(-1.58)	(-1.10)	(-1.01)
LOSS	+ / -	-0.770	-0.773	-0.685	-0.635	-0.585	-0.774	-0.684	-0.697	-0.636
		(-8.63)	(-8.67)	(-7.72)	(-7.39)	(-6.86)	(-8.68)	(-7.71)	(-7.98)	(-7.30)
NEWS	-	0.069	0.069	0.066	0.083	0.080	0.069	0.067	0.079	0.076
		(1.26)	(1.26)	(1.22)	(1.55)	(1.49)	(1.27)	(1.23)	(1.46)	(1.40)

Table 4 (Continued)

Variable	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BETA	+ / -	-0.463	-0.467	-0.319	-0.410	-0.309	-0.470	-0.321	-0.411	-0.303
		(-6.19)	(-6.23)	(-4.30)	(-5.42)	(-4.16)	(-6.28)	(-4.31)	(-5.48)	(-4.08)
ADISP	+ / -	-3.574	-3.581	-3.537	-3.786	-3.733	-3.586	-3.541	-3.695	-3.650
		(-7.28)	(-7.31)	(-7.21)	(-7.71)	(-7.59)	(-7.32)	(-7.22)	(-7.59)	(-7.49)
NUMEST	+	0.009	0.009	0.012	0.010	0.012	0.008	0.012	0.009	0.012
		(0.84)	(0.81)	(1.15)	(0.91)	(1.15)	(0.79)	(1.13)	(0.89)	(1.13)
FD	+	0.216	0.216	0.186	0.244	0.219	0.216	0.186	0.242	0.216
		(1.40)	(1.40)	(1.21)	(1.60)	(1.44)	(1.40)	(1.22)	(1.57)	(1.41)
Constant	+ / -	-0.346	-0.229	-0.084	-3.210	-2.798	-0.331	-0.225	-0.091	-0.092
		(-0.28)	(-0.18)	(-0.06)	(-2.28)	(-1.95)	(-0.26)	(-0.18)	(-0.07)	(-0.07)
Year and Industry FEs?		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		9,990	9,990	9,990	9,990	9,990	9,990	9,990	9,990	9,990
Adjusted R^2		0.233	0.233	0.235	0.238	0.238	0.233	0.235	0.236	0.237
Model F		20.02	19.68	19.11	19.67	19.05	19.68	19.11	19.41	18.85
Significance		<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Table 4 reports coefficients (t-statistics) estimating the following model using OLS:

$$FREQ_{it} = \beta_0 + [\ (\beta_1 * EQ_{it})\ or\ (\beta_2 * IEQ_{it} + \beta_3 * DEQ_{it})] + \beta_4 * RETVOL_{it} + \beta_5 * SPREAD_{it} + \beta_6 * CORR_{it} + \Sigma\, \gamma_k * Controls + \epsilon_{it}$$

FREQ equals then number of annual earnings forecasts issued during the fiscal year. *AQ* is total accruals quality, transformed using the Box-Cox transformation. *IAQ* (*DAQ*) is innate (discretionary) accruals quality obtained from decomposing *AQ* using the Francis et al. (2004; 2005) accruals quality decomposition. *AQ*, *IAQ*, and *DAQ* are scaled such that higher values correspond to higher quality accruals. *CORR* is the correlation between earnings and market adjusted returns over the 5 year period ending in t-1. *RETVOL* is the standard deviation of daily returns over fiscal year t-1. *SPREAD* is average daily bid-ask spread, scaled by the midpoint, over fiscal year t-1. *INSTOWN* is the percentage of shares owned by institutions as reported by Thomson-Reuters in the report issued closest, but prior to fiscal year end. *MVE* is the natural log of the market value of equity. *BIGN* is an indicator variable equaling 1 for any observation audited by a Big N auditor. *LIT* is an indicator variable equaling 1 for high litigation risk industries (SIC between 2833 and 2836, 8731 and 8734, 3570 and 3577, 7370 and 7374, 3600 and 3674, and 5200 and 5961). *MKBK* is the ratio of the market value of equity to the book value of equity. *LOSS* equals 1 if the firm reports negative earnings in fiscal year *t*. *NEWS* is an indicator equaling 1 if the firm reports an earnings-per-share increase from year *t-1* to year *t*. *BETA* comes from regressing daily firm returns on CRSP value-weighted market returns over the fiscal year. *ADISP* measures analyst forecast dispersion based on the latest earnings forecast issued in the fiscal year. *NUMEST* is the number of analyst estimates reported in the final First Call summary report prior to the firm's fiscal year end. *FD* equals 1 for any observation with fiscal year end after October 23, 2000. All continuous, unlogged, variables are winsorized at the first and 99th percentiles. T-statistics are based on standard errors clustered at the firm level. T-statistics greater than 2.58 (1.96, 1.645) in absolute magnitude signify significance at the p<0.01 (p<0.05, p<0.10) level (two-sided).

Table 5 – Effect of Earnings Quality on Forecast Horizon

		Continuous					Fractional Ranks			
Variable	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AQ	+ / -		-0.018	-0.031			-0.036	-0.064		
			(-0.86)	(-1.48)			(-0.83)	(-1.48)		
IAQ	+				0.201	0.132			0.199	0.126
					(3.38)	(2.16)			(3.21)	(2.00)
DAQ	-				-0.039	-0.045			-0.059	-0.071
					(-1.75)	(-2.06)			(-1.48)	(-1.76)
CORR	+			0.085		0.079		0.085		0.081
				(3.77)		(3.48)		(3.76)		(3.58)
RETVOL	+ / -			-8.472		-7.756		-8.484		-7.700
				(-5.93)		(-5.36)		(-5.94)		(-5.33)
SPREAD	+ / -			-1.788		-2.374		-1.846		-2.182
				(-0.99)		(-1.31)		(-1.02)		(-1.20)
INSTOWN	+	0.313	0.315	0.264	0.315	0.265	0.315	0.265	0.313	0.265
		(5.29)	(5.32)	(4.39)	(5.31)	(4.39)	(5.33)	(4.40)	(5.28)	(4.39)
LNMVE	+	0.096	0.099	0.068	0.071	0.048	0.099	0.068	0.072	0.050
		(7.56)	(7.65)	(4.68)	(4.76)	(3.01)	(7.61)	(4.67)	(4.74)	(3.08)
BIGN	+	0.051	0.051	0.057	0.037	0.047	0.051	0.057	0.040	0.050
		(0.90)	(0.91)	(1.02)	(0.66)	(0.84)	(0.91)	(1.02)	(0.71)	(0.88)
LIT	+ / -	-0.147	-0.146	-0.119	-0.137	-0.115	-0.146	-0.119	-0.138	-0.117
		(-2.10)	(-2.08)	(-1.69)	(-1.98)	(-1.65)	(-2.09)	(-1.70)	(-2.00)	(-1.68)
MKBK	+ / -	-0.010	-0.010	-0.009	-0.008	-0.007	-0.010	-0.009	-0.008	-0.007
		(-2.27)	(-2.37)	(-2.08)	(-1.66)	(-1.59)	(-2.36)	(-2.05)	(-1.78)	(-1.67)
LOSS	+ / -	-0.394	-0.396	-0.336	-0.364	-0.317	-0.396	-0.335	-0.374	-0.324
		(-8.70)	(-8.74)	(-7.34)	(-8.14)	(-7.00)	(-8.74)	(-7.33)	(-8.34)	(-7.13)
NEWS	-	-0.004	-0.004	-0.001	-0.001	0.001	-0.003	-0.001	-0.001	0.002
		(-0.19)	(-0.18)	(-0.04)	(-0.05)	(0.07)	(-0.18)	(-0.03)	(-0.04)	(0.08)

Table 5 (Continued)

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BETA	+ / -	-0.152	-0.154	-0.080	-0.140	-0.078	-0.154	-0.080	-0.138	-0.077
		(-5.49)	(-5.57)	(-2.83)	(-5.10)	(-2.76)	(-5.57)	(-2.85)	(-5.01)	(-2.71)
ADISP	+ / -	-1.609	-1.616	-1.563	-1.669	-1.605	-1.616	-1.562	-1.653	-1.592
		(-6.94)	(-6.98)	(-6.79)	(-7.24)	(-7.00)	(-6.98)	(-6.79)	(-7.15)	(-6.93)
NUMEST	+	-0.002	-0.002	0.001	-0.002	0.001	-0.002	0.001	-0.002	0.001
		(-0.63)	(-0.68)	(0.18)	(-0.59)	(0.18)	(-0.68)	(0.18)	(-0.60)	(0.17)
FD	+	0.103	0.102	0.091	0.109	0.097	0.102	0.091	0.110	0.098
		(1.07)	(1.06)	(0.95)	(1.14)	(1.02)	(1.06)	(0.96)	(1.15)	(1.03)
Constant	+ / -	-1.023	-0.968	-0.581	-1.647	-1.088	-1.020	-0.666	-0.947	-0.627
		(-4.87)	(-4.44)	(-2.44)	(-5.94)	(-3.67)	(-4.87)	(-2.91)	(-4.38)	(-2.68)
Year and Ind FEs?		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		9,990	9,990	9,990	9,990	9,990	9,990	9,990	9,990	9,990
Likelihood Ratio χ^2		2,433.47	2,435.19	2,520.59	2,462.25	2,534.67	2,435.08	2,520.57	2,458.53	2,530.76
Significance		<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Table 5 reports coefficients (z-statistics) estimating the following tobit model:

$$HORIZON_{it} = \begin{cases} \beta_0 + [\,(\beta_1 * EQ_{it}) \text{ or } (\beta_2 * IEQ_{it} + \beta_3 * DEQ_{it})] + \beta_4 * RETVOL_{it} + \beta_5 * SPREAD_{it} + \beta_6 * CORR_{it} + \Sigma\, \gamma_k * Controls + \epsilon_{it} \text{ if } HORIZON_{it} > 0 \\ 0 \text{ if } HORIZON_{it} \leq 0 \end{cases}$$

HORIZON equals then number of days between the first forecast and earnings announcement of fiscal year *t* earnings, divided by 365. For non-forecasting firms, *HORIZON* is set to 0 and then treated as a censored observation for estimation purposes. *AQ* is total accruals quality, transformed using the Box-Cox transformation. *IAQ* (*DAQ*) is innate (discretionary) accruals quality obtained from decomposing the Box-Cox transformed *AQ* using the Francis et al. (2004; 2005) accruals quality decomposition. *AQ*, *IAQ*, and *DAQ* are scaled such that higher values correspond to higher quality accruals. *CORR* is the correlation between earnings and market adjusted returns over the 5 year period ending in t-1. *RETVOL* is the standard deviation of daily returns over fiscal year t-1. *SPREAD* is average daily bid-ask spread, scaled by the midpoint, over fiscal year t-1. *INSTOWN* is the percentage of shares owned by institutions as reported by Thomson-Reuters in the report issued closest, but prior to fiscal year end. *MVE* is the natural log of the market value of equity. *BIGN* is an indicator variable equaling 1 for any observation audited by a Big N auditor. *LIT* is an indicator variable equaling 1 for high litigation risk industries (SIC between 2833 and 2836, 8731 and 8734, 3570 and 3577, 7370 and 7374, 3600 and 3674, and 5200 and 5961). *MKBK* is the ratio of the market value of equity to the book value of equity. *LOSS* equals 1 if the firm reports negative earnings in fiscal year *t*. *NEWS* is an indicator equaling 1 if the firm reports an earnings-per-share increase from year *t-1* to year *t*. *BETA* comes from regressing daily firm returns on CRSP value-weighted market returns over the fiscal year. *ADISP* measures analyst forecast dispersion based on the latest earnings forecast issued in the fiscal year. *NUMEST* is the number of analyst estimates reported in the final First Call summary report prior to the firm's fiscal year end. *FD* equals 1 for any observation with fiscal year end after October 23, 2000. All continuous, unlogged, variables are winsorized at the first and 99th percentiles. Z-statistics are based on standard errors clustered at the firm level. Z-statistics greater than 2.58 (1.96, 1.645) in absolute magnitude signify significance at the p<0.01 (p<0.05, p<0.10) level (two-sided).

Table 6 – The Effect of Institutional Owners on the Demand for High Quality Information

VARIABLE	Predicted Sign	(1) OCCUR	(2) OCCUR	(3) FREQ	(4) FREQ	(5) HORIZON	(6) HORIZON
IAQ	+	0.172	0.109	0.805	0.688	0.019	0.012
		(1.72)	(1.04)	(4.01)	(3.13)	(2.16)	(1.34)
DAQ	-	-0.077	-0.096	-0.133	-0.138	-0.006	-0.008
		(-2.15)	(-1.98)	(-1.94)	(-1.57)	(-2.05)	(-1.77)
DINSTOWN x IAQ	+		0.130		0.248		0.013
			(1.92)		(1.80)		(2.29)
DINSTOWN x DAQ	+ / -		0.035		0.005		0.002
			(0.57)		(0.05)		(0.42)
DINSTOWN	+	-0.070	-0.659	-0.154	-1.276	-0.006	-0.066
		(-1.22)	(-2.19)	(-1.42)	(-2.16)	(-1.20)	(-2.54)
Control Variables?		Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry FEs?		Yes	Yes	Yes	Yes	Yes	Yes
Observations		9,990	9,990	9,990	9,990	9,990	9,990
Model Test Statistic[a]		880.921	885.816	18.829	18.632	2537.520	2547.388
Significance		0.000	0.000	0.000	0.000	0.000	0.000

[a] Statistic is Wald's χ^2 (F, Likelihood Ratio χ^2) for columns 1 and 2 (3 and 4, 5 and 6).

Table 6 presents coefficients (test statistics) from estimating the following probit (OLS, tobit) model, where DV = *OCCUR* (*FREQ*, *HORIZON*)

$$DV_{it} = \beta_0 + \beta_1 * IEQ_{it} + \beta_2 * IEQ_{it} * DINSTOWN_{it} + \beta_3 * DEQ_{it} + \beta_4 * DEQ_{it} * DINSTOWN_{it} + \beta_5 * DINSTOWN_{it} + \beta_6 * RETVOL_{it} + \beta_7 * SPREAD_{it} + \beta_8 * CORR_{it} + \Sigma\, \gamma_k * \text{Controls} + \epsilon_{it}$$

OCCUR is an indicator equaling 1 in any fiscal year in which a firm makes a forecast of any future year's earnings. *FREQ* equals then number of annual earnings forecasts issued during the fiscal year. *HORIZON* is the number of days between the forecast date and earnings announcement date. *IAQ* (*DAQ*) is innate (discretionary) accruals quality obtained from decomposing *AQ* using the Francis et al. (2004; 2005) accruals quality decomposition. *AQ*, *IAQ*, and *DAQ* are scaled such that higher values correspond to higher quality accruals. *DINSTOWN* is an indicator value equaling one for observations above the annual median in institutional ownership. Control variables are included estimation, but results are not reported for brevity. All continuous, unlogged, variables are winsorized at the first and 99th percentiles. Test statistics are based on standard errors clustered at the firm level. Test statistics greater than 2.58 (1.96, 1.645) in absolute magnitude signify significance at the p<0.01 (p<0.05, p<0.10) level (two-sided).

Table 7 – The Effect of External Verification on the Demand for High Quality Information

Variable	Predicted Sign	(1) OCCUR	(2) OCCUR	(3) FREQ	(4) FREQ	(5) HORIZON	(6) HORIZON
IAQ	+	0.239	0.223	0.880	0.726	0.025	0.023
		(2.11)	(1.86)	(3.76)	(2.84)	(2.67)	(2.36)
DAQ	-	-0.092	-0.115	-0.155	-0.103	-0.007	-0.009
		(-2.38)	(-2.28)	(-2.10)	(-1.10)	(-2.22)	(-2.11)
DABFEES x IAQ	+		0.025		0.300		0.002
			(0.32)		(1.88)		(0.39)
DABFEES x DAQ	+ / -		0.043		-0.108		0.003
			(0.63)		(-0.87)		(0.61)
DABFEES	+	0.085	-0.033	0.195	-1.193	0.009	-0.002
		(1.72)	(-0.09)	(1.99)	(-1.69)	(2.14)	(-0.08)
Control Variables?		Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry FEs?		Yes	Yes	Yes	Yes	Yes	Yes
Observations		7,735	7,735	7,735	7,735	7,735	7,735
Model Test Statistic[a]		661.94	661.65	17.13	16.78	1,742.12	1,743.09
Significance		0.000	0.000	0.000	0.000	0.000	0.000

[a] Statistic is Wald's χ^2 (F, Likelihood Ratio χ^2) for columns 1 and 2 (3 and 4, 5 and 6).

Table 7 presents coefficients (test statistics) from estimating the following probit (OLS, tobit) model, where DV = *OCCUR* (*FREQ, HORIZON*)

$$DV_{it} = \beta_0 + \beta_1 * IEQ_{it} + \beta_2 * IEQ_{it} * DABFEES_{it} + \beta_3 * DEQ_{it} + \beta_4 * DEQ_{it} * DABFEES_{it} + \beta_5 * DABFEES_{it} + \beta_6 * RETVOL_{it} + \beta_7 * SPREAD_{it} + \beta_8 * CORR_{it} + \Sigma\, \gamma_k * \text{Controls} + \epsilon_{it}$$

OCCUR is an indicator equaling 1 in any fiscal year in which a firm makes a forecast of any future year's earnings. *FREQ* equals then number of annual earnings forecasts issued during the fiscal year. *HORIZON* is the number of days between the forecast date and earnings announcement date. *IAQ* (*DAQ*) is innate (discretionary) accruals quality obtained from decomposing *AQ* using the Francis et al. (2004; 2005) accruals quality decomposition. *AQ, IAQ,* and *DAQ* are scaled such that higher values correspond to higher quality accruals. *DABFEES* is an indicator value equaling one for observations above the annual median in abnormal audit fees (Ball et al. 2012). Control variables are included estimation, but results are not reported for brevity. All continuous, unlogged, variables are winsorized at the first and 99th percentiles. Test statistics are based on standard errors clustered at the firm level. Test statistics greater than 2.58 (1.96, 1.645) in absolute magnitude signify significance at the p<0.01 (p<0.05, p<0.10) level (two-sided).

Table 8 – Decomposing AQ

	Predicted Sign	*(1) Untransformed AQ*	*(2) Box – Cox Transformed AQ*
SIZE	-	-0.002	-0.101
		(-14.98)	(-12.67)
CFVOL	+	0.011	0.075
		(6.83)	(3.40)
SALEVOL	+	0.005	0.204
		(8.03)	(7.83)
OPCYCLE	+	0.000	0.016
		(0.54)	(2.69)
NEG	+	0.002	0.091
		(21.41)	(33.83)
INT	+	0.000	-0.009
		(2.54)	(-1.72)
INTDUM	+ / -	0.001	-0.018
		(3.20)	(-1.92)
CAP	-	-0.009	-0.639
		(-10.69)	(-17.78)
Intercept	+ / -	0.026	-3.655
		(22.20)	(-35.74)
Average Box-Cox λ		N/A	0.025
S.E.(λ)		N/A	0.013
Average N		3,296	3,296
Average Adj. R^2		0.377	0.433

Table 8 presents average coefficient estimates and t-statistics (in parentheses) from regressing either untransformed (column 1) or transformed *AQ* on determinants of innate *AQ* for years 1995 to 2010. *AQ* is the standard deviation of firm residuals for years t-5 to t-1 obtained cross-sectional estimations of the modified Dechow-Dichev model of accruals quality estimated for each year and industry having more than 20 observations (Dechow and Dichev 2002; McNichols 2002). Transformations of *AQ* are based on annual, maximum likelihood estimations of the Box-Cox power transformation (Box and Cox 1964). *SIZE* is the natural log of assets; *CFVOL* is the standard deviation of operating cash flows from year t-5 to t-1, scaled by assets; *SALEVOL* is the standard deviation of sales from t-5 to t-1, scaled by assets; *OPCYCLE* is the natural log of the firm's operating cycle; *NEG* is the sum of the number of fiscal periods in which the firm reported a loss over the prior 5 years; *INT* is intangibles intensity in year t; *INDUM* is an indicator variable equality 1 for any observation where Compustat reports a missing value for R&D and advertising expense; *CAP* is capital intensity in year t. T-statistics are computed using annual coefficient estimates (Fama and MacBeth 1973). T-statistics exceeding 2.947 (2.131, 1.753) in absolute value are significant at the $p<0.01$ ($p<0.05$, $p<0.10$) level.