TWO ESSAYS IN FINANCIAL ACCOUNTING

1. THE ASSOCIATION OF EARNINGS QUALITY WITH FINANCIAL ANALYSTS’ EARNINGS FORECAST ATTRIBUTES

2. THE INFLUENCE OF EARNINGS QUALITY ON FINANCIAL ANALYSTS’ HERDING BEHAVIOR

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ABSTRACT OF THE DISSERTATION

Two Essays in Financial Accounting

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Essay 1: The Association of Earnings Quality with Financial Analysts’ Earnings

Forecast Attributes.

This study investigates the association between firms’ earnings quality and analysts’ forecast errors and dispersion. The findings suggest that the quality of earnings is inversely related to analysts’ forecast errors but is not associated with forecast dispersion. These results are better understood by an examination of the relationship of forecast error and dispersion with the major sub-components of earnings quality— the quality of the innate accrual component (quality of accruals related to the complexity of the firm’s operations) and the quality of the discretionary accrual component (quality of managements’ judgment as reflected in accruals used to project future performance).

The inverse association between earnings quality and forecast error is driven primarily by the quality of the firm’s innate accrual component (InnAQ). As firm complexity and variability increase, earnings contain larger amounts of management judgment and estimation. The larger amount of management estimation included in earnings renders it relatively less reliable and thus forecasting difficulty (reflected in greater forecast errors and dispersion) is amplified for poorer InnAQ. This inverse association is the dominant effect in earnings quality’s association with analysts’ forecast errors.
The quality of firms’ discretionary accrual components depends upon whether managers use of their discretion to provide value relevant information, or whether they use the discretionary component to incorporate manipulative and noisy discretionary accruals.

In a regression of the of firms’ discretionary earnings components on forecast dispersion I find an inverse relationship between the magnitude of the firm’s discretionary earnings component and analysts’ forecast dispersion. This is consistent with managers using the discretionary component to provide information on firm performance, thus facilitating more precision in analysts’ forecasts.

This essay contributes to two controversial areas of accounting research. The study indirectly provides evidence supporting managers’ (on average) use of their discretion to provide value relevant information in earnings; and it simultaneously demonstrates analysts’ expertise in incorporating information related to EQ and its sub components into their forecasts.

**Essay 2: The Influence of Earnings Quality on Financial Analysts’ Herding Behavior.**

Essay 2 investigates how firms’ EQ and its innate (the quality of accruals related to the complexity of the firm’s operations) and discretionary (the quality of accruals based on managements’ discretion) sub-components affect analysts’ motivation to issue herding forecasts.

Herding forecasts are forecasts which mimic those issued by other analysts and ignore the analyst’s own private information. Although theoretical studies have linked
herding behavior to analysts’ rational reputational concerns, herding reduces the information available to investors in the market and hence negatively impacts market efficiency. Conversely, bold forecasts, forecasts issued which move away from the consensus (linked in prior studies to greater private information release and higher accuracy) are likely to contribute to improved market efficiency.

As capital market intermediaries, financial analysts are charged with facilitating investors’ investment decisions. The literature documents that poor earnings quality reduces investors’ ability to evaluate firm performance. This essay contributes to the literature by providing evidence on how financial analysts’ herding behavior is influenced by EQ and its sub components.

Results show that the quality of the firm’s innate accrual component is the major driver of analysts’ bold forecasting. The negative association between forecast boldness and firms’ innate accrual quality indicates that analysts issue bolder forecasts when investors have more difficulty determining firm value (noisier signal from innate accrual component). Given the prior literature finds that bolder forecasts contain more private information and are more accurate, the results suggests that analysts are effectively performing their market intermediary function.

The lack of a significant association between bold forecasting and the discretionary earnings component is in line with prior literature’s documentation of analysts’ poor utilization of the discretionary information in their forecasts. However, this study’s evidence of a positive association between bold forecasts and analysts’ firm specific experience implies that analysts with more firm specific experience have a
greater understanding of managers’ discretionary signals and exploit their advantage by issuing bolder forecasts.

Results show a negative association between firms’ overall EQ and analysts’ forecast boldness implying that analysts herd more the higher the firm’s EQ. This finding underscores the importance of reputational concerns and the demand for analysts’ investment advice for analysts’ herding behavior.
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It has taken a number of years, and entailed a lot of sacrifice and it has changed my life and the lives of my children. But change is the only thing that’s assured in this life….so I’ll do my part to make this change worthwhile…not only for my children Danielle and Dominic, and my for family…but also for my students and for others whom may come across my path.

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PREFACE

This dissertation investigates two related issues, (1) the association between earnings quality and financial analysts’ forecast attributes, and (2) the influence of earnings quality on financial analysts’ herding behavior.

Because the underlying theories for these two topics are different, the examination of the topics is presented as two separate essays. However, as both essays focus on earnings quality and the work of analysts, the literature review and certain sections of the research design (for example the descriptions of proxies used in both essays) have some overlap. The differences between the essays emanate from their motivation, methodology, findings and conclusions which are detailed in each essay.
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ESSAY 1: THE ASSOCIATION OF EARNINGS QUALITY WITH FINANCIAL ANALYSTS’ EARNINGS FORECAST ATTRIBUTES.

1. INTRODUCTION

This study investigates the association between a firm’s earnings quality and the forecast errors and dispersion made by analysts following the firm. Here, earnings quality (EQ) refers to the ability of reported earnings to be a faithful representation of actual firm performance as well as a valuable predictor of the firm’s future earnings. Specifically, the paper examines how earnings quality and the quality of its sub components (the innate component -related to firm complexity and the discretionary component –related to management discretion) affect sell-side analysts’ accuracy and their agreement on forecast earnings.

The reporting and forecasting of earnings are important capital market activities that influence the flow of economic resources. William Donaldson (then chairman of the Securities and Exchange Commission (SEC)), in an address to the London School of Economics in 2005, highlighted the need for high quality reporting in vibrant capital markets:

‘When investors buy shares in a company or purchase its debt securities, they must have faith that the company's financial statements ... accurately reflect the company's financial condition. ... as it becomes extremely time-consuming for investors to distinguish the good from the bad, they will tend to invest in other markets or perhaps not invest at all. This is of particular concern in the U.S...’

Investors depend heavily on financial analysts to help them ‘distinguish the good from the bad’ in terms of their investment decisions. Schipper (1991) describes analysts as financial intermediaries who aggregate both financial and non financial information to derive estimates of earnings.
An empirical investigation of the association between earnings quality and forecast characteristics therefore provides evidence on the effectiveness of financial analysts as information intermediaries, and also documents the importance of earnings quality and its subcomponents (the innate and the discretionary elements) on analysts’ forecasting effectiveness.

Prior literature has examined the impact of some disclosure quality measures on analysts’ forecast accuracy and dispersion (e.g. Lang and Lundholm, 1996; Barron et al., 1999, Bowen et al. 2002 and Francis et al. 1997), however this study is the first to specifically test the associations of earnings quality and its subcomponents, with the characteristics of analysts’ forecasts.

I focus on earnings because it is one of the most important financial metrics (Graham et al., 2005) and has been shown in the literature to have substantial predictive ability (Dechow et al., (1998); Barth et al., (2001)). Not surprisingly therefore earnings and earnings-related information are important inputs into analysts’ forecasts (Previts and Bricker, 1994).

Following Francis, LaFond, Olsson and Schipper (2005) (FLOS) I use the variability of the mapping of accruals onto cash flows (based on the Dechow and Dichev, 2002 measure) in a five year period as an inverse measure of the firms’ accrual/earnings quality. Using this proxy, $\text{Std}_\text{AQI}$ of accrual quality, consistent with FLOS, I determine how much of its variability is driven by the firm’s economic fundamentals (innate factors) and how much emanates from managements’ discretionary choices (discretionary factors).
Accruals contain the estimates and judgments introduced by management into earnings. Prior literature focuses heavily on the discretionary component of accruals. Its findings suggest that management uses their discretion in accruals to not only communicate relevant performance measurement information to users (Subramanyam, 1996) but also to manipulate earnings for opportunistic reasons (Jones, 1991; Healy and Wahlen, 1999).

The nature of the association between EQ’s discretionary component and forecast errors and dispersion, therefore, is not clear. If on average management use their discretion in earnings to make accruals that are informative about future performance, then forecast errors and dispersion will be inversely related to the size of the discretionary accrual component. However, if discretion is used, on average to make manipulative or noisy accruals, then forecast errors and dispersion would be directly related to the magnitude of the discretionary accrual component.

The innate accrual component will similarly have an important influence on forecast characteristics. Firm complexity, e.g. long operating cycles, increases the amount of estimation, allocation and judgment in earnings which may lead to reported earnings being relatively less reliable as a measure of performance and future earnings. Dechow and Schrand (2004) referring to firms’ complex operating environments state that some firms by the nature of their business can have low earnings/accrual quality, even in the absence of intentional earnings management.

The accuracy or legitimacy of accruals therefore is an important dimension of earnings quality. The quality of the discretionary component depends on whether management discretion is used to give value relevant information or to manipulate
earnings. The quality of the innate component depends on whether the complexity of the firm’s operations and the resulting level of estimation and judgment it contains render it less reliable as an indicator of actual and future firm performance.

My tests examining the association between earnings quality and forecast errors find, as hypothesized, that earnings quality is inversely associated with forecast errors. This result therefore provides empirical evidence of the importance of earnings quality for analysts’ forecast accuracy; suggests that analysts are effective users of the information in earnings; and suggests that one consequence of poor earnings quality is less accurate forecasts, or alternatively, a benefit of high quality reporting is more accurate analysts’ forecasts.

Also in line with expectations, I find that firms with more complex innate factors are associated with higher forecast errors and higher forecast dispersion. This result is consistent with complex innate factors reducing the predictive value of reported earnings and thereby increasing analysts’ forecasting challenges.

Interestingly, I find an inverse association between the absolute value of the discretionary accrual component and forecast error, consistent with higher magnitudes of managements’ discretion being associated with lower forecast errors. This inverse relationship has two important implications which contribute to issues being debated in the literature.

First it implies that firms on average use the discretionary component of earnings to provide users with value relevant information (consistent with Subramanyam (1996)); and second that analysts as expert financial statement users are able to correctly
interpret this discretionary information and incorporate it into their earnings forecasts, thereby lowering forecast error.

Though I do not find a significant association between forecast dispersion and my overall earnings quality measure $\text{Std}_AQI$, this can be explained by an offsetting of the (opposite) associations that the innate and discretionary earnings components have with forecast dispersion. While higher values of the innate component (more complexity) are associated with higher forecast dispersion, higher values of the discretionary component are associated with lower forecast dispersion.

This implies that as innate factors grow (reflected by larger values of $\text{InnAQ}$), dispersion increases. On the other hand, dispersion is reduced when earnings contain larger discretionary components. This outcome therefore, provides inferences consistent with those drawn from my tests on forecast error. Greater complexity in firms’ innate characteristics increases analysts’ forecasting challenges evidenced here by larger errors and higher dispersion. Larger discretionary components however, reduce forecast errors and dispersion, which suggests that on average firms provide value relevant information that facilitates analysts’ forecasting accuracy and agreement.

I extend my analyses to investigate whether analysts are able to distinguish between firms with informative $DAQ$ and those with noisy $DAQ$. Using firms that increased / (reduced) the variability of the earnings signal with their discretionary accrual components to proxy for firms that have noisy/(informative) discretionary earnings components, I find that analysts forecast errors and dispersion are only reduced for this sample of firms with ‘informative’ discretionary components. This inverse association suggests that analysts are able to use the information provided by managers of firms with
informative discretionary components to improve their forecasts; and also that analysts are able to ‘see through’ the manipulative and noisy \( DAQ \) of firms which use discretionary accruals to garble the earnings signal.

These findings are relevant to and contribute to several streams of the financial reporting literature.

1. I find an inverse association between earnings quality and forecast errors. This provides empirical evidence that confirms the importance of earnings quality as a factor which affects analysts’ forecasting accuracy.

2. The results suggest that analysts’ have the expertise to not only distinguish between informative and noisy \( DAQ \), but also that their forecasts prove that they are not fooled by managerial opportunism. This serves as one justification of investors’ heavy reliance on analysts in the capital markets, and adds to the literature on analysts’ expertise and knowledge of accruals which is disputed in the literature (Ettredge et al., 1995; Bradshaw et al., 2001).

3. The essay contributes to the earnings management literature by showing that in a large cross section of firms, there are some with informative discretionary accruals (consistent with Subramyam, 1996) and others with opportunistic or noisy accruals (Guay et al., 1996).

4. I find that the quality of the firm’s discretionary earnings component is an important determinant of the association between \( DAQ \) and analysts’ forecast characteristics. Where \( DAQ \) is informative, then \( DAQ \) is inversely related to forecast error and forecast dispersion; while where \( DAQ \) is noisy
there is no statistically significant association between $DAQ$ and forecast error or dispersion. This contributes to the literature documenting the consequences of poor versus high earnings quality.

This remainder of this essay is organized as follows. Section 2 provides a review of the related literature, Section 3 develops the hypotheses, and the research design is described in Section 4. The results of the study are discussed in Section 5, and my conclusion is presented in Section 6.
2.0 LITERATURE REVIEW

2.1 EARNINGS

2.1.1 The Significance of the Earnings Number

The reporting and forecasting of earnings are important capital market activities that influence the flow of economic resources. These activities are inter-related, and this dissertation investigates how the quality of reported earnings affects the sell-side analyst’s forecasts and production of private information.

I choose to focus on earnings because of its singular importance as a source of information in the capital market. Penman (2003, p.81) states that the market focuses on earnings as a primary summary statistic. The importance of earnings is again highlighted in Graham et al. (2005)’s survey of financial executives who report that they see earnings as the most important financial metric.

2.1.2 Perspectives for measuring the Quality of Earnings

Dechow and Schrand (2004) suggest that a high quality earnings number should do three things:

1. reflect current operating performance,
2. be a good indicator of future operating performance, and
3. accurately annuitize the intrinsic value of the company, (that is, be useful as a summary measure for assessing firm value).

This definition of high quality earnings draws several parallels to Levitt (1998)’s concept of meaningful disclosure. By giving users an indication of current operating performance, future operating performance and a measure of the firm’s intrinsic value
managers are able to tell investors, as Levitt (1998) says, the story of ‘where the company has been, where it is and where it will be going’.

A review of the financial reporting literature shows that there are a number of desirable bases on which earnings quality can be evaluated. These bases, usually judged from a decision usefulness approach, include attributes such as persistence (Lev, 1983), predictive ability (Lipe, 1990), smoothness (Luez et al. 2003), sustainability (Revsine et al., 1999), timeliness (Ball et al., 2000); conservatism (Basu, 1997), value relevance (Barth et al., 2001), and accrual quality (Jones, 1991).

Despite the importance of earnings, there is no universally accepted definition of what constitutes high quality earnings. Larcker and Richardson (2004) note that there are divergent views on what constitutes ‘high quality earnings’ but state that earnings quality is best defined knowing the use to which the accounting earnings will be put. There are many desirable quality dimensions (such as - persistence, predictive ability, smoothness, conservatism, value relevance, accrual quality) but earnings quality must be considered from the user’s objective.

Two of the analyst’s primary objectives include the related activities of forecasting future earnings and valuing the firm. Prior research examining the prediction of future cash flows has found that earnings better predict future operating cash flows than current operating cash flows (Dechow, Kothari and Watts (1998)). Further, Barth, Cram and Nelson (2001) find that the cash flow and the accrual components of current earnings have substantial more predictive ability for future cash flows than several lags of aggregate earnings.
Financial analysts, being engaged in earnings forecasting and firm valuation, should therefore have a significant interest in earnings and its components—accruals and cash flows. As predictive ability is enhanced by the breakdown of earnings into accruals and cash flows, the accuracy, or quality of accruals should be an important measure of earnings quality for analysts (given that accruals, rather than cash flows, contain management judgment). The quality/accuracy of accruals therefore should be significant to analysts in their forecasting and private information production activities.

This is confirmed by Barker and Imam (2008) who find that accounting based information relating to earnings quality (e.g. accrual versus cash flow composition) exerts a significant influence in the analysis and recommendations is analysts’ reports.

2.1.3 Judgment in Earnings – Opportunism vs Private Information releases

Generally Accepted Accounting Principles (GAAP) give managers flexibility to exercise judgment in making estimates / accruals to be included in earnings. The objective is to have an earnings number that better reflects firm performance in the reporting period. Dechow and Dichev (2002 p. 35) for example states that ‘One role of accruals is to shift or adjust the recognition of cash flows over time so that the adjusted numbers (earnings) better measure firm performance.’ Accruals therefore impact the “informativeness” of earnings.

Healy and Wahlen (1999) state ‘Management's use of judgment in financial reporting has both costs and benefits.’ The costs include management’s ability to include estimates that do not reflect the firm’s underlying economics in order to ‘manage earnings’ opportunistically to further their own interests. This results in the garbling of reported earnings (Watts and Zimmerman, 1986) and ultimately in an inefficient
allocation of economic resources. On the other hand, the benefit of giving managers
discretion includes the ability for managers to communicate their private information on
future firm performance which adds to the informativeness of earnings and ultimately to
improving resource allocation decisions.

Badertscher, Collins and Lys (2007) refer to these two widely held views as the
‘Opportunistic’ perspective (OP) and the ‘Information’ perspective (IP). In the
opportunistic perspective, managers use discretionary accruals to enhance their personal
welfare by disguising the firm’s true economic performance. Under this view
discretionary accruals will provide misleading information to financial statement users.
On the other hand, under the information perspective, managers use discretionary
accruals to reveal private value relevant information about the firm’s future prospects.
Here discretionary accruals will therefore increase the information contained in earnings.

Many studies have found that discretionary accruals are opportunistic. Most of
this evidence however has been detected in settings where the incentive for managers to
‘manage earnings’ is likely to be very strong, for example before an equity issuance
(Teoh, Welch and Wong, 1998a, 1998b), prior to management buyouts (Perry and
Williams, 1994), to meet financial analysts’ expectations (Burgstahler and Eames, 2003),
to benefit from compensation contracts (Holthausen et al, 1995) or to avoid violation of
loan covenants (DeFond and Jiambalvo, 1994).

Evidence supporting the information perspective has also been found in prior
research. Subramanyam (1996) concludes that on average the market attaches value to
discretionary accruals because the discretionary component increases the ability of
earnings to reflect fundamental value. Altamuro, Beatty and Weber (2005) find that

1 See Healy and Wahlen,(1999) for a review of the earnings management literature.
revenue recognition practices of including revenue prior to completion of the earnings process on average provided value-relevant information. Louis and Robinson (2005) also find that managers use their reporting discretion prior to stock splits to signal their private information.²

Healy and Wahlen (1999) in their review of the earnings management literature, point out that while prior research helps investors to be aware of the likelihood of earnings management, there is not enough evidence on how pervasive earnings management (opportunistic and/or private information transfer) is.

Guay et al. (1996, p.104) conjectures that ‘[g]iven managerial discretion over accruals has survived for centuries, our prior is that the net effect of discretionary accruals in the population is to enhance earnings as a performance indicator.’ Both Guay et al.(1996) and Healy (1996)’s discussion of that paper concur that in broad samples both the opportunistic and information perspectives of accruals will be encountered in a cross-section of firms, as well as within one firm over time, based on the differing incentives managers face in reporting earnings.

The two views on the use of managerial discretion lead to differing implications for the predictive usefulness of accruals (and earnings) in forecasting future cash flows (Badertscher et al., 2007). While there is still not enough evidence on how widespread either view is in the population, it has been noted by many studies that accruals improve the predictive ability of future cash flows (e.g. Barth, Cram and Nelson, 2001) which could suggest that ‘on average’ accruals play an informational role.

2.1.4 Accruals Quality

² Other research promoting the information perspective for managerial discretion include both empirical and theoretical studies (see Watts and Zimmerman, 1986; Demski 1998; and Ayra et al. 2003).
Dechow and Schrand (2004) state that some companies by the nature of their business will have low earnings [or accruals] quality even in the absence of intentional [opportunistic] earning management. Despite following the spirit of GAAP, companies with complex firm characteristics (such as volatile cash flows, high standard deviations in sales, long operating cycles and/or firms large in asset size with number of divisions) will have poor quality earnings due to the number of, and the difficulty of accurately making estimates to be included in earnings.

Francis, LaFond, Olsson and Schipper, 2005 (FLOS) refers to these accruals relating to the firm’s business model and operating environment as *Innate* accruals. They are viewed as distinct from those relating to managerial discretion (for either opportunistic or information based reasons), which consistent with the existing literature are termed *Discretionary* accruals.

Therefore, whilst opportunistic earnings management is a source of poor accruals quality it is not the only source. Managerial errors due to the inclusion of poor estimates in earnings are another primary source of poor quality accruals. Dechow and Schrand (2004) make the point that ‘estimation errors reduce earnings persistence’ (because they must be corrected in future earnings) and are irrelevant for valuation.

2.1.5 Innate vs. Discretionary Accruals

The quality of earnings is directly related to the amount and quality of management judgment and estimation included in accruals. FLOS state that ‘accruals reflect both economic fundamentals (innate factors) and managerial choices (discretionary factors)’.
More complex firm characteristics make it inherently more difficult for managers to accurately estimate accruals and therefore make it unlikely for them to achieve a good mapping of their accruals into cash flows. Examples include firms with high intangible assets (e.g. research and development), firms operating in high tech industries with products with short life spans, high growth firms, or firms trading in volatile markets. Poor innate accruals therefore lead unequivocally to a reduction in the information content of earnings.

Unlike innate accruals however, the accruals relating to discretionary factors may either increase or reduce the information content of earnings, depending on whether managerial discretion is used to include value relevant performance information or whether discretion is used to promote managers’ opportunistic motivations.

In predicting future earnings and firm value, accrual quality is important and as Dechow and Schrand (2004) state ‘an astute analyst cannot focus on earnings alone, but must also assess the quality of earnings’.

2.2 ANALYSTS

This study provides further evidence on the importance of earnings as a summary performance measure in the capital market. Additionally it sheds new light on the significance of the quality of earnings to analysts (a very important group of financial statement users) in their forecasting activities.

2.2.1 Impact on the Capital Market

Gogoi (2001) reports that in October 1999 when Tyco’s analyst published a newsletter accusing the company of providing misleading disclosures about its
acquisitions, investors questioned the credibility of Tyco’s disclosures and its stock price fell precipitously.

Sell side analysts’ output (forecasts, price targets and stock recommendations) are important in the capital market. Not only do they influence price (Francis and Soffer, 1997 find that analysts’ reports influence investors and hence market returns) but they also influence managers’ reporting of earnings. Graham, Harvey and Rajgopal (2005)’s survey of 402 financial executives provides evidence consistent with managers being so focused on meeting analysts’ consensus forecasts that they are willing to give up positive NPV projects.

2.2.2. Impact of Earnings Quality on Analysts’ Forecast Accuracy and Forecast Dispersion

Studies have shown that analysts are rewarded for producing more accurate reports. Rewards include higher recognition, for example selection to the Institutional Investors All American team, or career advancement, Hong and Kubrik (2003). Stickel (1992) reports that the Institutional Investors All American team produces more accurate forecasts than other analysts, and infers that there may be a positive relationship between performance (forecast accuracy) and reputation and remuneration. Mikhail et al. (1999) finds that in his sample of analysts, turnover is lower among more accurate forecasters.

Ramnath, Rock and Shane (2006)’s review of the literature related to analysts’ forecasts and stock recommendations states that ‘[r]esearch on analysts’ earnings forecast accuracy has focused on two main attributes: 1) the nature of the forecast itself, for example, whether the forecast reflects new information or whether the analyst is merely
herding….and 2) characteristics of the analyst including….the analyst’s prior experience
and brokerage firm.’

There are a few studies in the prior literature which examine the impact of
disclosure on analysts’ forecast accuracy and dispersion. The results of these studies
imply that different types of disclosure may affect analysts’ accuracy in different ways.
While some studies report an inverse relationship between disclosure quality and forecast
accuracy, others do not document this association.

Lang and Lundholm (1996), using analysts’ ratings of firms’ disclosure, find that
higher rating are associated with more accuracy and less dispersion. Barron, Kile and
O’Keefe (1999)’s study using the MD&A section of the annual report also find that
higher quality disclosures are associated with lower forecast error and dispersion. This is
in line with Bowen, Davis and Matsumoto (2002) who find that conference calls increase
analysts’ ability to accurately forecast earnings.

On the other hand, some studies testing the association between disclosure quality
and forecast accuracy have not found this inverse relationship between disclosure quality
and analysts’ forecast errors and dispersion. Francis, Hanna and Philbrick (1997) report
that managers’ presentations to security analysts have no effect on analysts’ forecast
errors or dispersion. Healy, Hutton and Palepu (1999) also does not find a significant
association between forecast dispersion and sustained increases in firm disclosure
policies.

This dissertation examines the relationship between firms’ earnings quality and
the accuracy of the mean forecast and the dispersion of analysts’ forecasts. Earnings
quality is not only important as a form of disclosure, but is interesting as a disclosure
form in its own right, as an important summary statistic used by the market (Penman, 2003). Prior literature is limited in studies that investigate this association.
3.0 HYPOTHESIS DEVELOPMENT

3.1 How does the quality of earnings affect the accuracy of the analysts’ forecasts?

Dechow, Kothari and Watts (1998) provide evidence that earnings are a good predictor of future cash flows; while Barth, Cram and Nelson (2001) find that the components of earnings (accruals and cash flows) are even better predictors of future cash flows than earnings itself. Dechow and Schrand (2004) state that a high quality earnings number should be a good indicator of future operating performance.

As cash flows are more objectively determined (being realized) than accruals (being related to future events and are therefore uncertain and subject to managements’ estimation and allocation decisions), this study uses the quality of accruals as a proxy for earnings quality.

Management’s intervention into the earnings process through accrual estimation enables the accruals component to either improve or reduce the predictive ability of earnings depending on whether managers introduce informative or noisy accruals.

Given that the accrual component of earnings has significant predictive power, higher accruals quality in terms of accuracy and consistency should facilitate more accurate forecasting and thus lower forecast errors.

I therefore hypothesize that:

**H1 (A): Analysts forecast errors are inversely related to earnings quality.**

Dechow (1991) finds that firms with more complex characteristics (e.g. longer operating cycles, greater volatility in working capital requirements, and investment and financing activities) suffer more severely from cash flow timing and matching problems which reduce their ability to reflect firm performance. The quantum of accruals and
hence the amount of estimation and judgment required to make earnings a good signal of future earnings is amplified as the firm’s operating environment becomes more complex. Higher firm complexity therefore results in a lowering of the firm’s Innate Accrual quality.

Higher firm complexity, which is reflected by a lower quality of the innate accrual earnings component, increases analysts’ forecasting difficulty. As firm complexity increases, analysts must increase their knowledge of firm activities and model the growing number of variables related to firm business in their proprietary models in order to estimate the level of firms’ future earnings.

The greater firm complexity, the greater will be analysts’ difficulty in accurately forecasting earnings due to the lower level of reliability of the innate accrual signal analysts receive and the increase in the number of variables that need to be incorporated into proprietary models.

I therefore hypothesize that:

**H1(B): Analysts forecast errors vary inversely with the quality of innate accruals.**

Prior literature has found that managers use discretionary accruals to either communicate their private information, (which strengthens the earnings signal) or to distort the reporting of the firm’s true economic performance for opportunistic reasons, (which garbles the earnings signal).

If discretionary accrual component of earnings is informative (Subramanyam, 1996) that is managers use their discretion in accruals to provide users with information relevant for forecasting future earnings, then as a consequence, analysts forecasting
accuracy should improve. Thus a high quality discretionary accrual component will reduce forecast errors and produce an inverse association between forecast errors and discretionary accrual quality.

On the other hand, if discretionary accruals are noisy, (e.g. they are distorted by estimation errors and managerial opportunism (Watts and Zimmerman, 1986)) here discretionary accrual quality is low (noisy) and will not have predictive ability. Analysts’ forecast errors for firms with noisy discretionary accrual components should therefore on average increase as the quality of the discretionary component declines.

Analyst forecast errors therefore may either vary directly or inversely with the quality of the discretionary accrual component of earnings, depending on whether this earnings component is informative or noisy. I therefore state my hypothesis on this association in null form:

**H1 (C): Analysts’ forecast errors are not associated with the quality of firms’ discretionary accrual earnings component.**

### 3.2 How does the quality of earnings affect the dispersion of the analysts’ forecasts?

High quality earnings should provide a relatively precise signal of future earnings, leading to low forecast dispersion or more analyst agreement on the forecasted earnings number. This is in line with prior research. Lang and Lundholm, 1996 document that forecast dispersion is lower for firms with higher analysts’ disclosure ratings. Bowen, Davis and Matsumoto, 2002 also find that firms that made conference calls had lower forecast dispersion than firms which did not.
I reason that when the variance of the earnings signal is large analysts’ forecasts will be more widely spread reflecting higher forecast dispersion. The imprecision of the signal generates greater diversity of opinion (or analysts’ disagreement) on future earnings among analysts. Alternatively, when the variance of the signal is small, its precision facilities analysts’ agreement and hence lower forecast dispersion.

I therefore reason that as the earnings signal becomes stronger (e.g. as the quality of accruals increases) or clearer to analysts, forecast dispersion should decrease. The opposite should also be true- as the earnings signal weakens (becomes more noisy, e.g. as the quality of accruals declines) forecast dispersion should increase.

I therefore hypothesize that:

**H2 (A): Analysts forecast dispersion will vary inversely with earnings quality.**

Analysts use proprietary models to incorporate the fundamental economic characteristics of the firm and industry in order to produce their earnings forecasts. I reason that the more complex the firm’s characteristics, (for example the longer its operating cycle or the more uncertain it’s cash flows, or the greater the variability of its sales), the greater the opportunity for diversity in forecast earnings. Analysts’ models will reflect differences both in the analysts’ identification of the variables driving complexity as well as differences in the analysts’ translation of the implications of these complexity variables. The resulting variations in proprietary forecasting models should therefore lead to a wider range of forecast earnings.

I therefore hypothesize that:

**H2 (B): Analysts forecast dispersion is inversely related to the quality of firms’ innate accrual component.**
While some studies have found that firms’ discretionary accruals are on average informative (Subramanyam, 1996; Altamuro et. al., 2005; Louis and Robinson, 2005) the majority of the earnings management literature provides evidence of managers’ opportunistic use of discretionary accruals (Burgstahler and Eames, 2003; Holthausen et al., 1995; Jones, 1991). Healy and Wahlen 1999 state that a broad sample of firms should contain both firms with informative discretionary accruals (high quality DAQ) and also firms with opportunistic discretionary accruals (low quality DAQ).

Where DAQ is informative, analysts will receive a strong signal of future earnings and hence this should foster analyst agreement on forecast earnings. I therefore expect that when the discretionary component of earnings is informative, then forecast dispersion will be low and there will be a direct association between forecast dispersion and the value of the discretionary accrual component.

Where however the discretionary component of earnings is noisy, the earnings signal analysts receive will be garbled and weak. This imprecise signal should lead to a wider dispersion of forecasted earnings. If on average firms’ use the discretionary accrual component of earnings to manipulate earnings, then I expect an inverse association between forecast dispersion and the discretionary accruals earnings component.

Based on the above discussion, I state my hypothesis in null form:

H2 (C): Analysts forecast dispersion is not related to the quality of firms’ discretionary accrual component.
4.0 RESEARCH DESIGN

This section describes the variable measurement (4.1), empirical models (4.2), sample selection (4.3) and descriptive statistics (4.4) used in testing my hypotheses, and concludes with univariate results (4.5) of the tests performed.

4.1 VARIABLE MEASUREMENT

4.1.1 Dependent Variables

Analysts’ Forecast Error (Error)

Analysts’ forecast errors are defined as the absolute difference between the mean analysts’ forecast and actual reported annual earnings per share from I/B/E/S. Error, my proxy for forecast error, is the absolute value of the mean analysts’ forecast error. Error reflects how ‘far off’ the analysts’ mean forecast was from the actual EPS reported by managers.

Error = |Mean forecast – EPS|

Cheong and Thomas (2008)’s findings suggest that price deflation of forecast error and forecast dispersion is likely to result in biased coefficients. Based on these findings, I use both the un-scaled forecast error (Error) as well as a version scaled by share price (Error2) as proxies of forecast error. Further, in line with their recommendations I include share price as a regressor in my analyses that use the un-scaled version of forecast error (Error); and I include the inverse of price as an independent variable in regressions using the scaled proxy for forecast error (Error2).
Analyst Forecast Dispersion (*Disp*)

Analyst forecast dispersion is measured for each firm year as the standard deviation of analysts’ forecast estimates.\(^3\) Again, based on Cheong and Thomas (2008), I use both an un-scaled measure of dispersion, *Disp* and a measure scaled by share price, *Disp*\(^2\), to proxy for forecast dispersion. Again I include share price as a regressor in my analyses using the un-scaled proxy (*Disp*), and the inverse of price when the scaled dispersion proxy (*Disp*\(^2\)) is used.

*Disp* reflects the spread of the analysts’ forecast around the mean forecast. Smaller *Disp* therefore indicates that forecasts are distributed more closely around the mean presumably signifying greater agreement among analysts; while larger *Disp* reflects a wider distribution of forecasts around the mean forecast, indicating more disagreement among analysts on future earnings.

4.1.2 Independent Variables of Interest

Earnings Quality Proxy

The ability to predict next period’s earnings is likely to be greatly enhanced by both the accuracy of accruals as well as by the consistency of firms’ accrual quality. The accuracy of accruals and their reliability from period to period should therefore be important to analysts when relying on them to forecast earnings. My proxy for earnings quality, *Std_AQI*, reflects both accrual accuracy and consistency.

\(^3\) These forecasts of annual earnings for year t are made between the issue of year t-1’s annual results and year t’s 1st quarter results.
The \( \text{Std}_A Q I \) measure

The earnings quality measure, \( \text{Std}_A Q I \), is based on Dechow and Dichev’s (2002) measure of the quality of working capital accruals and earnings, modified by the inclusion of additional variables (i.e. \( PPE \) to account for non current accruals and \( \Delta \text{Rev} \) to control for volatility) as suggested in McNichols’ (2002) discussion of the model. \( \text{Std}_A Q I \) is the standard deviation of firm \( j \)’s residuals (in the five years \( t \) to \( t-4 \)) from annual cross-sectional regressions relating current accruals to cash flows (see equation 1 below):

\[
TCA_{j,t} = \phi_{0,j} + \phi_{1,j} \text{CFO}_{j,t-1} + \phi_{2,j} \text{CFO}_{j,t} + \phi_{3,j} \Delta \text{Rev} + \phi_{4,j} PPE + \nu_{j,t} \tag{1}
\]

Where:

Firm \( j \)’s total current accruals in year \( t \), \( TCA_{j,t} = (\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta \text{Cash}_{j,t} + \Delta \text{STDEBT}_{j,t}) \); \( \Delta CA_{j,t} \) is the change in firm \( j \)’s current assets (\( \text{Compustat} \#4 \)) between year \( t-1 \) and year \( t \) scaled by average total assets; \( \Delta CL_{j,t} \) is the change in firm \( j \)’s current liabilities (\( \text{Compustat} \#5 \)) between year \( t \) and year \( t-1 \) scaled by average total assets; \( \Delta \text{Cash}_{j,t} \) is the change in firm \( j \)’s cash resources (\( \text{Compustat} \#1 \)) between year \( t \) and year \( t-1 \) scaled by average total assets; and \( \Delta \text{STDEBT}_{j,t} \) = Firm \( j \)’s change in debt in current liabilities (\( \text{Compustat} \#34 \)) between year \( t \) and year \( t-1 \). Firm \( j \)’s cash flow from operations in year \( t \), \( \text{CFO}_{j,t} = \text{Compustat data item} \#308 \). \( \Delta \text{Rev} \) = firm \( j \)’s change in revenue (\( \text{Compustat} \#12 \)) between year \( t \) and year \( t-1 \) and \( PPE \) is firm \( j \)’s gross value of property, plant and equipment (\( \text{Compustat} \#7 \)) in year \( t \).

The residual, \( \nu_{j,t} \), represents current accruals that are not associated with cash flows in either the current year, previous year or in the next financial year. These

---

This proxy is also used by Francis, LaFond, Olsson and Schipper (2005) as their measure of accruals quality (\( AQ \)) measure.
unmatched accruals are assumed to be due to managements’ error in the estimates and judgments incorporated into earnings. The larger the residual, the higher the errors included in earnings.

Values of $\text{Std}_{AQIj; t} = \sigma(\upsilon_j)t$ (the five year standard deviation of the residual) are calculated for all firms with available data in the sample. $\text{Std}_{AQI}$ is a proxy of the variability of the firm’s earnings signal.

To be included in the tests of my hypotheses, requires that each firm-year observation has data on $\text{Std}_{AQI}$ and the necessary dependent variable measure. As $\sigma(\upsilon_j)t$ is based on five annual residuals, the sample is restricted to firms with at least 7 years of data (as Eq. (1) includes both lead and lag cash flows).

**Interpretation of the Std$_{AQI}$ measure**

Higher values of $\text{Std}_{AQI}$ reflect greater variability in accruals quality or poorer earnings quality, as future accruals (and earnings) will be more difficult to predict. As the study considers the quality of earnings from the perspective of the analyst’s forecasting decisions, it is the consistency of the residuals rather than their size that determines predictive ability and hence ‘quality’. Even where residuals are consistently large (but have a small standard deviation) accruals quality will be relatively high. Despite a poor mapping, a small standard deviation of residuals will allow analysts to better predict future earnings due to the relative consistency of accruals quality, thus facilitating analysts’ prediction of accruals and earnings. On the other hand, larger magnitudes of $\text{Std}_{AQI}$ signify greater uncertainty (less predictability) and hence increase the difficulty for analysts in forecasting accruals, future earnings and firm value.
Segregating Accruals into Innate (InnAQ) and Discretionary (DAQ) Accrual Quality Components

An added benefit of this accruals/earnings quality proxy is that it can be decomposed into measures of two earnings quality subcomponents. The first, the quality of the innate accrual component (InnAQ), that is, the quality of the accruals driven by the firm’s business model and operating environment; while the second reflects the quality of discretionary accruals component (DAQ), or the quality of managers’ discretion reflected in accruals.

To derive the quality metrics for these components, annual regressions of Std_AQI are run on the innate factors identified by Dechow and Dichev (2002) – firm size (Mean_size), standard deviation of cash flows from operations (Std_CFO), standard deviation of sales revenue (Std_Rev), length of operating cycle (LOOP) and the incidence of negative earnings realizations (Losses). The predicted value from each regression is used to estimate the firm’s innate accrual quality while the error serves as an estimate of discretionary accrual quality (Francis et al., 2005).

\[
Std_AQI = \delta + \delta Mean_size + \delta Std_CFO + \delta Std_Rev + \delta LOOP + \delta Losses + \epsilon \tag{2}
\]

Hence the firm’s earnings quality measure, Std_AQI, is segregated into two components. One component (the fitted values from equation 2) that relates the variability in accruals quality (Std_AQI) to the firm’s inherent operating environment, gives a measure of the firm’s innate accrual quality (InnAQ). The other component (the residual from equation 2) variability in accrual quality that is unrelated to firm characteristics is assumed to be the result of managements’ discretion- and therefore a proxy for the quality of the discretionary accruals component (DAQ).
Following FLOS, I use InnAQ, the fitted value of equation (2), as a proxy of the quality of the firm’s innate accrual component. InnAQ reflects the amount of accrual and cash flow ‘miss-match’ (variability in Std_AQI) that is predicted by the complexity of the firm’s operating environment. The more complex the firm, (and therefore the larger the amount of management estimation and judgment required in calculating the earnings number), the higher the value of InnAQ will be. As larger values of InnAQ reflect lower innate accrual quality, InnAQ is an inverse measure of innate accrual quality.

DAQ and absDAQ

DAQ measured as the residual of equation (2), represents the variability in accrual quality accorded to management discretion (or alternatively it is the difference between actual (Std_AQI) and predicted variability (InnAQ). Positive values of DAQ indicate that managers’ discretionary accruals increased the variability of Std_AQI earnings quality, while negative values indicate the opposite- managers’ discretionary accruals reduced the variability of Std_AQI.

The discretionary accrual component proxies for the deviation in analysts’ expectations of actual accrual variability from predicted variability based on innate firm characteristics. As analysts likely face the same difficulty in understanding deviations (whether positive or negative) from expected variability, I use the magnitude, that is the absolute value, of the discretionary component, absDAQ as a measure of the size of the discretionary accrual component. absDAQ therefore reflects the amount of variability in accrual quality due to managements’ discretion and serves as my proxy for the quality of the firm’s discretionary accrual earnings component.
4.1.3 **Control Variables**

I control for variables which have been shown in the literature to have an impact on the value of the dependent variables in my analyses. These include the size of the firm \((Ln\_Size)\), the number of analysts following the firm \((Following)\), the size of the earnings surprise at the prior year end \((Q4earnsp)\), the company’s financial performance \((ROA)\), whether the firm reports a loss \((Loss)\) and the age of the forecast \((Meanage)\).

Larger firms are likely to be more complex, manifested for example by more of product lines and operating divisions. Greater complexity increases information asymmetry resulting in greater analyst disagreement (higher forecast dispersion) and higher forecast errors.

I control for firm size by including \(Ln\_size\) measured as the natural logarithm of firm \(j\)’s average total assets as a regressor in my analyses. I expect that both analysts’ forecast error and dispersion will be positively associated with the earnings quality measures.

Barth, Kaznik and McNichols (2001) find that larger firms have higher analyst following. The number of analysts following the firm directly impacts the firm’s information environment. I include the variable \(Following\) (i.e. the number of firms following obtained from I/B/E/S) as a control for the information environment. Higher analyst following should result in more information on the firm, thereby reducing information asymmetry. I expect Following to be negatively related to forecast error and dispersion.

The size of firm \(j\)’s prior year’s earnings surprise \((Q4earnsp)\) gives an indication of the difficulty analysts’ have in forecasting the firm’s earnings (Barron et. al., 2002). Higher prior earnings surprises therefore proxy for greater forecast difficulty and should
therefore be associated with higher forecast errors and higher dispersion. I include a control for forecast difficulty $Q4earnsp$ in my analyses. $Q4Earnsp$, the earnings surprise on annual prior year earnings (based on fourth quarter estimates) is measured as the absolute difference between the mean forecast of annual earnings in the last quarter of year $(t-1)$ and the actual EPS in year $t-1$, expressed as a percentage of the prior year’s earnings $(t-1)$. $Q4earnsp$ is therefore hypothesized to be positively related to forecast error and dispersion.

$Meanage$, or the number of days between the date the forecast was issued and the date of the firm’s first quarter earnings announcement. The age of the forecast has been found to be negatively related to its accuracy, that is, more recent forecasts have been found to be more accurate.

$ROA$, the return on assets, is the annual percentage return on the firm’s average total assets. It is calculated by dividing the firm’s net income by its average assets and multiplying by 100.

Hayn (1995) finds that losses are less informative about a firm’s future prospects than profits; and Das and Somnath (1998) show that financial analysts’ forecasts are more accurate for non-loss making companies than for loss companies. I therefore control for losses using $Losses$, a qualitative variable which is set to 1 if the firm makes a loss in the financial year but is otherwise equal to 0.
4.2 EMPIRICAL MODELS

4.2.1 Empirical Model for Testing Hypothesis 1

Hypothesis 1 posits that analysts forecast errors are: H(1a) inversely related to earnings quality; H(1b) inversely related to the quality of the quality of innate accruals; and H1(c) not related to discretionary accruals.

The following models are employed to test the hypotheses:

H1(a)

\[
\text{Error}_{i,t} = \alpha + \beta_1 \text{Std}_{AQI} + \beta_2 \text{Q4EarnSp} + \beta_3 \text{Following} + \beta_4 \text{Meanage} \\
+ \beta_5 \text{Ln}_{\text{Size}} + \beta_6 \text{Losses} + \beta_7 \text{ROA} + \beta_8 \text{Price} + \epsilon
\]

(4) Model 1

H1(b&c)

\[
\text{Error}_{i,t} = \alpha + \beta_1 \text{InnAQ} + \beta_2 \text{absDAQ} + \beta_3 \text{Q4EarnSp} + \beta_4 \text{Following} + \beta_5 \text{Meanage} \\
+ \beta_6 \text{Ln}_{\text{Size}} + \beta_7 \text{Losses} + \beta_8 \text{ROA} + \beta_9 \text{Price} + \epsilon
\]

(5) Model 2

Predicted relationships for variables of interest:

H1(a)

The coefficient on $\beta_1$ is expected to be positive and significant showing that analysts’ errors are higher when earnings quality is lower (as reflected by higher values of Std_{AQI}).

H1(b)

The coefficient on $\beta_1$ (InnAQ) is expected to be positive and significant reflecting higher errors as InnAQ increases. Increases in InnAQ (i.e. reductions in the quality of the innate accrual component) result as firm complexity increases. Complexity leads to more estimation in earnings and thus reduces the quality of the innate accrual components. With less reliable accrual information analysts’ forecasts errors are likely to increase.

Theory supports both a positive and/or a negative association between forecast
error and the quality of the discretionary accrual component of earnings. If the
discretionary accrual component provides value relevant information (Subramanyam,
1996) then forecast errors should be lower (inversely related) the larger the size of the
firms’ discretionary accrual component- and therefore the coefficient on $absDAQ$ will be
negative. However, if the discretionary accrual component is based on managements’
opportunism then the relationship with forecast error will be a direct one and the
coefficient on $\beta_2$ ($absDAQ$) will be positive.

4.2.2 Empirical Model for Testing Hypothesis 2

Hypothesis 2 posits that analysts forecast dispersion is: H(2a) inversely related to
earnings quality; H(2b) inversely related to the quality of the quality of innate accruals;
and H2(c) not related to discretionary accruals.

The following models are employed to test the hypotheses:

H2(a)

\[
Disp_{it} = \alpha + \beta_1 \text{Std}_AQI + \beta_2 Q4EarnSp + \beta_3 \text{Following} + \beta_4 \text{Meanage} \\
+ \beta_5 \ln(\text{Size}) + \beta_6 \text{Losses} + \beta_7 \text{ROA} + \beta_7 \text{Price} + \epsilon
\]  
(6) Model 1

H2(b&c)

\[
Disp_{it} = \alpha + \beta_1 \text{InnAQ} + \beta_2 absDAQ + \beta_3 Q4EarnSp + \beta_4 \text{Following} + \beta_6 \text{Meanage} \\
+ \beta_7 \ln(\text{Size}) + \beta_7 \text{Losses} + \beta_8 \text{ROA} + \beta_9 \text{Price} + \epsilon
\]  
(7) Model 2
Predicted relationships for variables of interest:

\textit{H2(a)}

The coefficient on $\beta 1$ is expected to be positive and significant showing that analysts’ dispersion is higher for firms with lower earnings quality (as reflected by higher values of $Std_{AQI}$).

\textit{H2(b) & 2(c)}

The coefficient on $\beta 1 (InnAQ)$ is expected to be positive and significant reflecting the increased difficulty in forecasting analysts face as the firm’s operating environment increases in complexity. As complexity increases the quality of the innate accrual component of earnings declines as larger amounts of estimation and management judgment are incorporated into the earnings figure. This reduces the precision in accruals and therefore reduces the strength of next period’s earnings that analysts receive resulting in a wider range of forecasts. I therefore expect an inverse association between forecast dispersion and the quality of the firm’s innate accrual component, as reflected by a positive coefficient on $InnAQ$.

Forecast dispersion’s association with firms’ discretionary accrual earnings component depends on whether the firm’s managers use their discretion in earnings to provide value relevant information, or whether they use discretion for opportunistic motivations. If on average firms use the discretionary accrual component to communicate information then an inverse relationship evidenced by a negative coefficient on $absDAQ$ should result. However, if firms’ on average use their discretionary accrual components for manipulative reasons, then dispersion should be higher as the size of the firms’ discretionary component increases, evidenced by a positive coefficient on $\beta 2 absDAQ$. 
STATISTICAL TESTS

The study uses panel data - where observations include a set of firms over a number of years. It is therefore likely that the variables are both cross-sectionally and serially correlated. As such regression errors are unlikely to be independent and can create misspecified test statistics (Bernard, 1987).

To correct for both cross-sectional and time-series dependence I use two-way cluster (clustering by firm and by year) robust standard errors which the econometric literature shows provides a suitable control for both patterns of dependence (Petersen, 2008; Gow et al., 2009). For robustness I also include fixed effects year and industry dummies as the dataset covers 14 years and 40 industries.

Additionally, I estimate the model using generalized method of moments (GMM) because its low distributional assumptions make it appealing for use with panel data. GMM does not require zero covariance across years or homoskedasticity across firms for efficiency and therefore alleviates the cross-sectional correlation problems of panel data. GMM’s results are also robust where independent variables are correlated. Estimates and statistics (including White adjusted standard errors) from GMM estimation are efficient and robust to heteroskedasticity.

The results of the tests estimated using OLS with clustering of standard errors by firm-year are almost identical to those using GMM.

4.3 SAMPLE SELECTION

4.3.1 Sample of Analysts’ Forecasts used in the testing of the Hypotheses
All tests are based on I/B/E/S forecasts of annual earnings of year \( t \) issued after the release of the prior years’ annual financial statements but before the firm’s first quarter earnings are announced (See Figure 1 for timeline used for variable measurement). These restrictions increase the likelihood that analysts relied on the firm’s most recent annual report to produce their forecasts, that is, analysts use the financial statement information for year end \( t-1 \) to forecast year \( t \)’s earnings.

An added benefit of using forecasts made early in the financial year as per Barron, Byard and Kim, 2002, is that analysts are focused on forecasting core earnings (rather than any management manipulations of earnings). Finally, by limiting the sample to forecasts made in this relatively short period (a mean of 51 days), I avoid including stale forecasts (Brown and Kim, 1991) in the analysis.

The initial sample contains a total of 391,631 annual forecasts in the period 1992 – 2005 with the required earnings announcement dates for the prior year’s fourth quarter and the current year’s first quarter.

The study uses annual financial data from Compustat to for computing its earnings quality measures and control variables. The final sample consists of all the annual forecasts of firms for which the required earnings quality and control variable information was available on Compustat. It comprises 154,881 annual forecasts issued for 3,288 firms in 17,268 unique firm years between 1992 and 2005.

4.4 **DESCRIPTIVE STATISTICS**

Table 1 reports descriptive information about the variables. Panel (1) gives the descriptive statistics of the variables used in the final regressions and Panel (2) gives the
descriptive statistics on the sample firms used to derive the earnings quality variables based on FLOS (2005).

The mean and median values of $\text{Std}_A QI$ are 0.05 and 0.04 compared to 0.04 and 0.03 respectively in the FLOS sample. This implies that the average quality of earnings of the firms in my study is a little lower than those included in FLOS. My sample covers the years 1992 to 2005, a period in which there was a lot of concern about earnings quality, while the FLOS sample covers a longer period (from 1970 to 2001) for much of which there was not a lot of concern about earnings quality. The innate characteristics of sample firms used in deriving the earnings quality variables are compared to those in FLOS show that my sample firms are larger, have longer operating cycles, have less variability in sales and cash flows from operations but my sample firms have suffered more losses in the prior 10 year period (see Table 1 for supporting statistics).

The mean analyst following is 10.57 (median 8), the mean earnings surprise (absolute value) is 12%, sample firms earn a mean 3.83% return on mean assets which have a log of 6.63, and have suffered a mean of 1.8 losses in the prior 10 years.

Sample firms are relatively large, however this should only bias against my finding results due to the lower amount of variability than can be expected in the earnings quality variables.

4.5 **UNIVARIATE CORRELATION ANALYSIS**

Table 2 presents the Pearson correlation coefficients among the variables in the study. It reveals that Error is only significantly positive correlated to one earnings quality variable, the signed value of the discretionary accrual component $-DAQ$ (0.02
with a p-value of 0.013). Correlations between Error and the other earnings quality variables are both weak and insignificant. The correlation matrix also shows that Error is significantly positively related to Ln_size (firm size), Following (analyst following), Q4earnsp (the earnings surprise for the prior year’s results) and Losses.

Table 1 also shows that Disp, my proxy for forecast dispersion, is significantly negatively related to the earnings quality measures Std_AQI, InnAQ and DAQ, (but not with absDAQ). As higher values of the earnings quality variables signify poorer earnings quality, the negative correlation with forecast dispersion implies that analysts’ forecast dispersion is increased with lower values of Std_AQI and InnAQ or higher quality earnings. This is inconsistent with hypothesis 2.

As expected the earnings quality measures are themselves fairly strongly (and significantly) correlated. Std_AQI and InnAQ have a correlation coefficient of 0.54 (p-value<.0001); while Std_AQI and absDAQ have a coefficient of 0.58 (p-value<.0001); and absDAQ and InnAQ a coefficient of 0.37 (p-value<.0001).

Consistent with Cheong and Thomas (2008) I find a weak positive correlation between Price and each of my dependent variables- Error and Dispersion.

My multivariate tests provide additional evidence on the associations between the dependent variables and the independent variables of interest (earnings quality). These tests include controls for factors which are likely to affect the hypothesized associations (which are likely to confound my univariate results). Finding from the multivariate tests are documented in the next section, Section 5 – Results.
5.0 RESULTS

5.1 The Relationship between Analysts’ Forecast Errors and Earnings Quality

5.1.1 Association of Forecast Errors (ERROR) and Earnings Quality

Results of tests of Hypothesis 1(A)

Table 3 reports the results of equation (4) the regression of analysts’ forecast errors on earnings quality. Regression results show that, as predicted, \( Std_AQI \) the comprehensive measure of earnings quality is positively related to \( Error \), with a coefficient of 0.43 (\( p\text{-value}< 0.0001 \)). This is consistent with my prediction that higher levels of \( Std_AQI \) (i.e., poorer earnings quality) are associated with larger errors in analysts’ forecasts. The result is similarly reflected in the significant positive coefficient of \( Std_AQI \) in the regression using an alternative proxy for forecast error, \( Error_2 \), (coefficient 0.04, \( p\text{-value} 0.0104 \)).

These results therefore support H1 (A) which posits an inverse relationship between earnings quality and forecast error. This implies that analysts’ forecast accuracy is higher the higher the quality of firms’ earnings.

5.1.2 Association of Forecast Errors (Error) and Quality of the Innate Accruals

Earnings component (InnAQ) - Results of tests of Hypothesis 1(B)

Table 4 provides evidence consistent with expectations that forecast errors are inversely related to the quality of firms’ innate accrual earnings components. Specifically, regression results show \( InnAQ \) (an inverse measure of innate accrual quality) is positively related to forecast error, \( Error \) with a coefficient of 2.13 (\( p\text{-value}< 0.0001 \)). The result is corroborated by \( InnAQ \)’s highly significant positive association
with Error_2, when the alternative forecast error measure is used as the dependent variable.

This suggests that the lower the quality of firms’ innate accrual component (indicated by higher values of InnAQ) and reflecting greater firm complexity, the higher the mean analyst forecast error. This result is expected as complex firm characteristics (such as long operating cycles, high standard deviations of sales and cash flows and large firm size) compound both managements’ accrual estimation accuracy and analysts’ forecasting challenges. As the firm’s innate accrual quality decreases, the accrual and earnings information reported by management becomes less reliable with greater estimation. Analysts therefore forecast the earnings of these firms’ complex operating activities with less reliable accrual information, leading to higher forecast errors.

Results therefore confirm H1 (B)’s inverse relationship between forecast errors and the quality of the firm’s innate accrual component. The results also reflect that the quality of innate accruals, is very important for analysts’ forecast accuracy. The coefficient on InnAQ is much larger in terms of its magnitude and significance than the other regressors including absDAQ.

5.1.3 Association of Forecast Error (ERROR) and Discretionary Accrual Quality

(absDAQ) - Results of tests of Hypothesis 1(C)

Table 4 also reports the outcome of my tests of H1(C). The coefficient on absDAQ, the absolute value of the firms’ discretionary accrual earnings component, is
-0.39 \textit{(p-value 0.0241)}. The results of the regression, using the scaled \textit{(Error2)} forecast error measure also show that \textit{absDAQ}, with a coefficient of -0.05 \textit{(p-value 0.0231)} is negatively related to forecast error.

The negative association with forecast error indicates that higher magnitudes of firms’ discretionary accrual earnings components are associated with lower forecast errors. This result is consistent with managers, on average, using their discretion to provide value relevant information in earnings; and also with analysts being able to use this value relevant information in their forecasts to improve forecast accuracy.

5.1.4 Control variables

Tables 3 and 4 present a consistent picture of forecast error’s association with control variables (both forecast error measures reflect equivalent associations at the same levels of significance). Results of the tests of hypothesis H1 show that control variables are significantly associated with analysts’ forecast error (with the exception of \textit{ROA}) and the relationship is consistent across Tables 3 to 4. All are in the expected directions with the exception of \textit{Meanage} which is inversely related to \textit{Error}, signifying that older forecasts are more accurate. While this is not in line expectations or with prior research, it should be noted that the forecasts in the sample are made within a short time frame (between the release of the prior year’s financial results and the release of the first quarter’s results) during which no new financial data is released. (Many of the prior studies use a longer forecast period and include stale forecasts). The greater accuracy of earlier forecasts is reasonable if the experienced analysts who regularly follow the firm issue forecasts earlier than their less experienced counterparts. This would be in line
with Guttman (2010)’s theoretical prediction that, ‘all else equal, analysts with a higher precision of initial private information tend to forecast earlier, and analysts with a higher learning ability tend to forecast later.’

All other controls however are significant (at the .001 level) and in their hypothesized directions. Prior years earning surprise $Q4earnsp$ is positively associated with Error reflecting consistency in the challenge analysts’ face in forecasting firms’ earnings from period to period. Analyst following, Following, is negatively associated with Error, consistent with the mean forecast being more accurate the larger the number of analysts following the firm. Higher analyst following is often associated with a richer information environment which should facilitate more accurate forecasts or lower forecast errors. The size of the firm (Ln_size) is positively related to Error implying that analysts forecast accuracy is challenged as the size of firms grow as no doubt the complexity of the firms increase. As hypothesized Losses are positively related to Error reflecting the higher level of difficulty analysts face in forecasting the earnings of ‘loss’ firms due to the lower information content (Hayn, 1995) of reported losses as compared to profitable firms.

5.2 The Relationship between Analysts’ Forecast Dispersion and Earnings Quality

5.2.1 Association of Forecast Dispersion (Disp) and Earnings Quality (Std_AQI) -

Results of tests of Hypothesis 2(A)

Table 5 reports the results of estimating equation (6) using a generalized method of moments model with fixed effects dummies for year and industry and White adjusted standard errors to control for cross sectional correlation.
In both regressions, one using an un-scaled forecast dispersion dependent variable \((Disp)\), and the other using dispersion scaled by price \((Disp2)\), \(Std_AQI\)’s coefficient reflects an insignificant association with analysts’ forecast dispersion. A possible interpretation of this outcome is that earnings quality, specifically the variability in the accuracy of accruals, is not a significant factor contributing to the range of the earnings estimates forecast by analysts. This however is difficult to reconcile with prior literature which finds that accruals have significant predictive ability (Barth et al., 2001) and earnings quality has been found to exert a significant influence on the analysis and recommendations included in analysts’ reports (Barker and Imam, 2008).

A more plausible explanation for the anomalous result is that the two components of \(Std_AQI\) - innate and discretionary accrual components have opposite or offsetting effects on forecast dispersion which results in an insignificant relationship between \(Std_AQI\) and forecast dispersion. Results of hypotheses 2(B) and 2(C) which look at the association of each earnings quality sub component with forecast dispersion provide some confirmatory evidence of this. In a regression of the earnings quality sub-components on dispersion, the innate accrual component \(InnAQ\) has a positive association while \(absDAQ\) has a negative association with forecast dispersion.

5.2.2. Association of Forecast Dispersion and Innate Accruals Quality (InnAQ)

Results of tests of Hypothesis 2(B)

Table 6 shows that as hypothesized, there is an inverse association between innate accrual quality and forecast dispersion. Specifically, \(InnAQ\)’s has a highly significant positive association with forecast dispersion, as reflected in both regressions. Using the
un-scaled dispersion measure $Disp$ as the dependent variable, $InnAQ$ has a coefficient of $0.57$ ($p$-value $< 0.0001$); and with the scaled measure $Disp^2$ as dependent variable $InnAQ$ has a coefficient of $0.03$ ($p$-value $0.0033$).

This direct relationship suggests that as firm complexity increases and the quality of the innate accrual earnings component declines (reflected by higher values of $InnAQ$) analysts’ disagreement increases as evidenced by higher forecast dispersion. Complexity increases the number of variables that affect firms’ earnings and increases the level of estimation and imprecision in earnings. The less precise accrual/earnings signal coupled with the increased number of variables that need to be incorporated into analysts’ proprietary models increases the diversity in analysts’ estimates.

As hypothesized therefore, results confirm that forecast dispersion is inversely related to innate accrual quality.

5.2.3 Association of Forecast Dispersion with Discretionary Accruals Quality
- Results of tests of Hypothesis 2(C)

Table 6 also reports the results of $absDAQ$’s association with forecast dispersion. The $absDAQ$ variable (proxying for the quality of the discretionary accruals earnings component) has a significant negative coefficient of -0.01 ($p$-value $0.0302$) in the regression with $Disp^2$ (forecast dispersion scaled by price). The inverse relationship implies that as the size of the firm’s discretionary accrual component increases (in absolute terms), the amount of dispersion in analysts’ forecasts declines. This result is consistent with firm managers’ using the discretionary accrual earnings component to communicate value relevant information to users- (as concluded from my tests using
forecast error). If analysts use this value relevant information, then the signal of future earnings will be more precise as the size of the discretionary accrual component increases, leading to more agreement amongst analysts on forecast earnings and hence less dispersion.

This inference however is only weakly supported by \textit{absDAQ}'s association with \textit{Disp}, the un-scaled proxy of forecast dispersion when \textit{absDAQ} is regressed on \textit{Disp}. The coefficient (-0.08) is only significant at the 10% level of significance. I conduct further analysis to better understand this association.

\textit{Additional Tests}

Guay et al., 1996 states that a large cross section of firms over a long period is likely to include firms with discretional accrual components that (1) enhance earnings’ ability to reflect performance; (2) reflect opportunism, or (3) are noisy.

Firms that use their discretionary accrual components to provide value relevant information should have lower information asymmetry between managers and analysts and thus benefit from reduced forecast dispersion. On the other hand, firms whose managers use their discretion to introduce noisy or manipulative accruals should not benefit from reduced dispersion. Instead these firms may have no association between the discretionary component and forecast dispersion (e.g. where discretionary component is noisy) or there may be a positive relationship between the level of the discretionary component and forecast dispersion (e.g. where the discretionary component is manipulative).

I anticipate my sample having firms with discretionary components with all three characteristics, and try to identify firms with informative discretionary components and
firms with opportunistic discretionary components. I test for hypothesized cross-sectional differences in the association between forecast dispersion and firms with noisy versus informative discretionary accrual components, in order to validate the results of my tests.

I divide the samples’ firm year observations into treciles based on the signed value of the discretionary accrual component. Firms in the lowest trecile of $DAQ$ values all have negative values, signifying that managers used discretionary accruals to reduce variability in the earnings signal ($Std_{AQI}$). Using discretionary accruals to reduce the variability in accruals quality is consistent with managers trying to improve predictive ability. As this objective is in line with providing value relevant information, I use this lowest trecile of DAQ as a proxy for firms with ‘informative’ discretionary accrual components.

On the other hand, firms in the trecile with the highest $DAQ$ values use discretionary accruals to increase (or garble) the variability of the earnings signal ($Std_{AQI}$). As this is consistent with managers’ reducing the predictive ability of earnings and is in line with having a manipulative or noisy discretionary accrual component, I use this trecile as a proxy for firms that have ‘manipulative or noisy’ discretionary accrual components.

I run equation (7) separately on each of these sub-samples (firms with the highest and lowest treciles of $DAQ$ values). Table 7 highlights the results of, and difference between, the associations of forecast dispersion with firms with informative $DAQ$ values (lowest $DAQ$ values) and firms with manipulative $DAQ$ values (highest $DAQ$ values).
Dispersion is significantly inversely related to $absDAQ$ for the firms assumed to have informative discretionary components. Here the coefficient on $absDAQ$ is -0.37 with a $p$-value of 0.0388. This implies that analysts’ use the information in the discretionary accrual components of these firms to reduce dispersion, and hence is consistent with informative discretionary quality. It should be noted that regardless of sub-sample, $InnAQ$ has a significantly positive association with forecast dispersion.

However firms in the regression using the other sub-sample of firms assumed to have noisy/manipulative discretionary accrual components, $absDAQ$ is not associated with $Disp$ (coefficient -0.02, $p$-value 0.7449). This is consistent with analysts not being able to use the information in the discretionary accrual earnings components of these firms to reach greater consensus on forecast earnings.

I use the sub-samples to test whether the results hold for the association with forecast error. Table 8 provides additional evidence confirming the cross-sectional differences between the forecast error’s associations with firms’ informative versus manipulative discretionary accrual components. Specifically, $absDAQ$ has a significantly negative association with $Error$ (coefficient -1.85, $p$-value < 0.0001) in the sub sample of firms with informative discretionary accrual components. The negative association indicates that higher $absDAQ$ is associated with lower forecast errors. In the other sub sample, $absDAQ$ has an insignificant association with $Error$ (coefficient -0.01, $p$-value 0.9773). Again there is little difference in $InnAQ$’s significantly positive association with forecast error in each of the two sub samples.

This test therefore demonstrates how differences in managers’ objectives affect firms’ accrual quality and has consequences for analysts’ forecast accuracy and
dispersion. Firms with informative discretionary accrual income components provide information that analysts are able to use to improve forecast accuracy and reduce the dispersion in their forecasts.

The study also highlights the fact that in a large sample of firms, on average, firms use their discretion to provide users with value relevant information.

5.2.4 Control variables

Associations between control variables and forecast dispersion are consistent across Tables 5 - 7. Results show that all control variables are significantly associated (at the 0.05 level or better) in the hypothesized directions, with the exception of analyst following which is not significantly associated with dispersion in Table 7.

5.3 Sensitivity Tests- Alternative Earnings Quality Proxy

The earnings management literature relies heavily on the Modified Jones Model as a proxy for earnings quality. Many studies have used this measure and found high or low abnormal accruals when managers have incentives to manipulate earnings for opportunistic reasons. For example, researchers using the Jones Model based measures have found that firms had abnormal levels of accruals that enabled them to: reduce regulatory costs, [Jones (1991)]; increase management compensation, [Guidry et al. (1998)]; overstate earnings prior to public securities offerings, [Teoh, Welch and Wong (1998a and 1998b)].

While the Jones Model proxies have been validated in earnings management studies, as a measure of earnings quality that can be relied upon by analysts forecasting future earnings, I foresee a number of short-comings. First, the measure is computed for
a single period. Healy (1996) notes that managers use of discretion in accruals can be expected to shift over time based on the incentives they face. Using a single period as a measure of a firm’s earnings quality is risky as it may not be representative of the firm’s ‘true’ quality. Analysts as experts would therefore likely use a multi year quality measure.

The Jones model has also faced criticism over the potential to classify ‘normal’ accruals as ‘abnormal’ accruals. The model assumes that the level of accruals depend only on changes in credit sales and the value of property, plant and equipment and assumes accruals are similar for all firms in the same two-digit SIC industry grouping.

Bernard and Skinner (1996) point out that this is a very broad classification of firms which could include dissimilar firms with very different levels of normal accruals. They illustrate this with an example from SIC industry 35 which includes both makers of heavy equipment for the oil and gas industry as well as makers of video games. Bernard and Skinner (1996) conclude that discretionary accruals estimated by the Modified Jones Model are likely to include non-discretionary components. This may result in a study’s ‘estimated’ abnormal or discretionary accruals being correlated with performance measures such as future cash flows or forecast errors or dispersion.

I use the Modified Jones Model, to create an additional proxy for earnings quality. I calculate absDA_roa the firm’s absolute abnormal accruals based on the Modified Jones Model adjusted for firm performance as recommended by Kothari et al. (2005). Testing the correlation between the Jones Model earnings quality measure and the FLOS measures, I find that absDA_roa is most closely correlated with my measure of the quality of the innate accrual quality, InnAQ (correlation coefficient 0.36, p-value
<.0001), then to the overall quality measure *Std_AQI* (correlation coefficient 0.29, *p*-value <.0001) and least to the measure of the quality of the discretionary accrual component *absDAQ* (correlation coefficient 0.15, *p*-value <.0001).

The results of tests on the association of tests *absDA_roa* with *Error* are given in Table 9 while tests on the association with *Disp* are reported in Table 10. The results show a positive relationship between *absDA_roa* and both forecast error and forecast dispersion.

I interpret this as indicating that analyst forecast errors and dispersion are higher for firms with higher levels of discretionary accruals in earnings. This is again consistent with poor earnings quality increasing the challenges faced by analysts in their forecasting activities.
6.0 CONCLUSION

This essay investigates the association between firms’ earnings quality and analysts’ forecast errors and dispersion. Using an accrual based earnings quality proxy adopted from FLOS 2005 which facilitates the segregation of earnings quality into its subcomponents - innate accrual quality (the quality of accruals related to the complexity of the firm’s operations) and discretionary accrual quality (the quality of accruals based on managements’ discretion), I investigate how earnings quality and the quality of its subcomponents are related to forecast errors and dispersion.

I find evidence consistent with higher quality earnings being associated with lower analyst forecast errors, or an inverse relationship between earnings quality and analysts’ forecast errors. My results also suggest that the sub-components of earnings quality- the innate component (accruals related to the firm’s economic fundamentals), and the discretionary component (accruals related to management discretion) also have significant impacts on analysts’ forecast errors and dispersion.

As hypothesized, I find greater complexity in firms’ innate factors is associated with larger analysts’ forecast errors and dispersion, implying that firms’ innate accrual components are directly related to forecast characteristics.

I find that the discretionary earnings component has the opposite association with forecast characteristics. Larger values of the discretionary component are associated with lower forecast errors and dispersion, suggesting an inverse relationship between discretionary quality and forecast error and dispersion. This is consistent with firm managers using their discretion to incorporate value relevant information into earnings,
thus facilitating more consensus and accuracy in analysts’ earnings estimates (Subramanyam, 1996).

This finding is also consistent with analysts being able to interpret and use the information in management’s discretionary accruals. The results of additional tests are consistent with analysts being able to distinguish between firms with informative discretionary accrual components and those with manipulative accrual components.

The significant inverse association between discretionary accrual quality and forecast error and dispersion for firms in the lowest treecile of $DAQ$ values (i.e. firms that used their discretionary earning components to lower the variability in the earnings signal, and thus are more likely to proxy for firms with informative discretionary accrual quality) suggests that analysts use the value relevant information contained in discretionary accrual quality of these firms to reduce their uncertainty and improve the accuracy of their forecasts. This is consistent with Subramanyam, 1996’s finding that discretionary accruals contain information about future earnings.

On the other hand, when discretionary accruals are noisy, (firms with the highest treecile of $DAQ$ values) there is no association between $DAQ$ and either forecast error or dispersion suggesting that analysts do not systematically use $DAQ$ in estimating future earnings. This implies that analysts are not ‘fooled’ by noisy $DAQ$’s opportunistic and noisy discretionary accruals.

Given that results show that analysts can identify innate and discretionary quality; that they can distinguish between firms with noisy discretionary components and those with informative discretionary accrual components - my results lend support to analysts
being expert financial statement users and provides some justification for their significant influence in the capital market.

The prior literature provides mixed evidence on analysts’ expertise in understanding accruals. While some studies promote the analyst’s expertise (Ettredge et al. 1995) others show that analysts (like investors) do not understand the information in accruals (Bradshaw et al., 2001). This essay therefore adds to the literature by providing evidence in support of their expertise in recognizing and using accrual quality in their forecasting activities.

The study also adds to the discussion on two important debates in the earnings management literature. First, my results suggest that consistent with Guay et al., 1996 and Healy 1996, firms with both informative and noisy discretionary accruals in my sample provides support for Guay et al., 1996’s statement that both are likely to be found in a large cross section of firms. Further I find that on average firms use the discretionary component of earnings to provide value relevant information to users.

There are however important potential limitations to the inferences that can be drawn from the study. The validity of any measure of earning quality is dependent on the soundness of the model estimating these unobservable characteristics. As such all conclusions and inferences made in the study are dependent on the accuracy of the accrual models used in assessing earnings quality.
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ESSAY 2 – THE INFLUENCE OF EARNINGS QUALITY ON FINANCIAL ANALYSTS’ HERDING BEHAVIOR

1. INTRODUCTION

This study examines the impact of earnings quality on the ‘boldness’ of analysts’ forecasts. Forecast boldness is a measure of the private information analysts release in their forecasts. Bolder forecasts reflect the release of larger amounts of analysts’ private information, while ‘herding’ forecasts reflect the release of smaller amounts of the analyst’s private information. Consistent with this, Clement and Tse (2005) find that bold forecasts are on average more accurate than herding forecasts.

Herding occurs when analysts only partially reveal their private information and instead mimic the forecasts of other analysts or the consensus forecast. This practice reduces the information revealed in individual analyst’s forecasts. As information reflected in analysts’ reports affect security prices (Francis and Soffer, 1997) herding can therefore exacerbate the problem of inefficient market prices. On the other hand, bold forecasts can increase private information flow into the market as well as shorten the time taken for it to be incorporated into security prices.

Theoretical studies predict that analysts herd for reputational reasons, career concerns and due to low self-assessed forecasting abilities (Scharfstein and Stein, 1990; Trueman, 1994). Scharfstein and Stein (1990)’s model shows that agents will produce more herding forecasts when they believe that their private information is different from that of other analysts. Trueman (1994) predicts that the boldness of analysts’ forecasts increases with their self assessed ability; and that more confident analysts produce bolder forecasts while less confident analysts produce forecasts close to the consensus.
One role of financial analysts, as capital market intermediaries and sophisticated users of financial statements, is to help investors ‘distinguish the good from the bad’ in terms of their stock market investments. Despite the significant influence analysts have in the market, their expertise and/or independence has been questioned both in the academic literature and in the financial press. These concerns were further heightened by analysts’ failure to detect irregularities before the market decline in 2002, or before the ‘tech stock bubble’ in the 1990’s, and more recently, before the financial industry’s near-collapse in the 2007-2008 period.

This study is motivated by the need to better understand the sell side analysts’ value as intermediaries in the capital market, as well as to determine how firms’ earnings quality affects analysts’ reports. Opaque accounting reports have been widely blamed in the press and in the congressional hearings on the Enron bankruptcy as one reason why analysts did not uncover the financial irregularities. This study seeks to gain an understanding of the factors relating to earnings quality that motivate analysts to fully reflect their private information; and conversely, the factors that inhibit analysts from fully disseminating their private information in their forecasts.

Managers’ ability to manipulate earnings is widely viewed as the root cause of opaque financial reporting. A large body of research has studied management’s use of discretion in earnings. A number of these studies have provided evidence consistent with managers using discretionary accruals to manipulate earnings for opportunistic reasons (see for example Healy and Wahlen, 1999’s review of the earnings management literature). On the other hand, some studies have provided evidence consistent with
managers using their discretion in earnings to incorporate value relevant information through discretionary accruals (Subramanyam, 1996).

In a large sample of firms there will be diversity in firms’ discretionary components of accrual quality (discretionary components). FLOS (2005) and Guay et al. (1996) predict that some firms will have discretionary components that add value relevant information, while others will have noisy discretionary components. As investors have difficulty understanding the information in the discretionary component (Sloan, 1996; Xie, 2003), investors are more likely to rely on analysts’ investment advice the larger the firm’s discretionary component. The high demand for information gives analysts greater incentive to produce more accurate (or bolder) forecasts in order to enhance their reputations for accuracy, increase their client base and hence their compensation.

Analysts more confident in their ability to understand managements’ discretionary information are therefore likely to incorporate value relevant discretionary information into their forecasts making them more accurate and bolder. Therefore if on average firms’ discretionary components are informative there should be a positive association between the size of the discretionary component and the boldness of analysts’ forecasts indicating that larger amounts of discretionary information will increase analysts’ bold forecasting.

Where analysts’ do not understand managers’ discretionary messages, and/or when the discretionary signal is noisy Plumlee (1993)’s results imply that analysts will reduce their use of the ‘complex’ information. This suggests that when the discretionary component is on average noisy, firms’ discretionary components will not be significantly associated with analysts’ forecast boldness.
Firms’ low quality discretionary components, coupled with analysts’ documented low level of comprehension of the discretionary earnings component (Bradshaw, Richardson and Sloan, 2001; Xie, 2001) are likely to lead to a muting of the association between forecast boldness and the discretionary accrual component. That is, the positive association (between forecast boldness and the discretionary component) expected for firms’ with informative discretionary components is likely to be offset or muted by the lack of an association of firms with noisy discretionary components. I therefore hypothesize and test the null hypothesis that there is no significant association between forecast boldness and firms’ discretionary accrual component.

While the discretionary component may present a challenge to analysts, analysts with more firm specific experience should develop a better understanding of firm performance and of the reliability of managements’ judgment and discretionary signaling. Analysts with more firm specific experience therefore are more likely to understand managements’ discretionary information. Given that these analysts have longer track records reflecting their forecasting ability, they should also be less inhibited by career concerns (Hong et al., 2000) and more confident in incorporating managements’ discretionary information and issuing bolder forecasts. I therefore test the hypothesis that analysts with more firm specific experience have a stronger (more positive) association between forecast boldness and firms’ discretionary accrual component than their peers.

While the literature focuses on the discretionary component’s association with opaque reporting, not much attention has been devoted to the role of the innate accrual component, (the other EQ component which measures accrual quality based on the variability and complexity of firm operations) in opaque accounting. However, Dechow
and Schrand (2004) state that ‘some companies by the nature of their business will have low earning quality even in the absence of intentional earnings management.’ Their study suggests that firms’ with complex and variable operational characteristics may also contribute to opaque reporting since the earnings of these firms contain high levels of estimation, management judgment and accruals which reduce the reliability of the earnings figure. FLOS (2005) find that this innate component is larger than the discretionary component and has a significant influence on EQ.

When innate accrual quality is poor, the signal of future earnings is weak and investors are likely to have difficulty predicting future earnings. Thus, investors are likely to rely more heavily on analysts’ advice the lower the innate accrual quality. Faced with high investor demand analysts are likely to have more incentive to enhance their reputations as higher relative rankings could result in larger increases in their client base, commissions and other compensation.

Increased compensation has been linked to more accurate forecasting which enhances the analyst’s reputation relative to his peers and increases the chance of being more highly ranked in the annual Institutional Investor poll (Stickel, 1992). As Clement and Tse (2005) find that bolder forecasts are more accurate, analysts have a higher incentive to differentiate themselves as having high forecasting ability by reflecting more of their private information and issuing bolder forecasts the lower the firms’ innate accrual quality. I therefore hypothesize that analysts’ forecast boldness is inversely associated with innate accrual quality.

Having examined how both the innate and discretionary subcomponents of EQ affect the boldness of analysts’ forecasts (or their herding behavior) in hypotheses 1 and
2, Hypothesis 3 then studies the association between analysts’ forecast boldness and overall EQ. Overall EQ’s association with forecast boldness will be influenced by the relationships of both of its sub-components’ (the innate and the discretionary) associations with forecast boldness. Given that the larger sub-component, the innate component is hypothesized to have a negative association with forecast boldness, and that the discretionary component is hypothesized to not have a significant association (due to diversity in both the informativeness of the component and in analysts’ skill in understanding managements’ discretionary information), I hypothesize that overall, EQ’s association with forecast boldness will be driven by the innate component. I therefore hypothesize that there is an inverse association between a firm’s EQ and the boldness of its analysts forecasts.

The hypotheses are tested at the level of the individual forecast (examining the association between the firm’s EQ and the boldness of the individual analyst’s forecasts); and at firm level (examining the association between the firm’s EQ and the collective boldness of all forecasts made by analysts issuing forecasts for the firm during the forecast period). Based on prior research, I measure the boldness of the individual analyst’s forecast as the distance of the forecast from the prior consensus (Clement and Tse, 2005). For the firm level perspective, I measure herding with Mensah and Yang (2008)’s ‘herding index’, a distributional measure based of the actual percentage of the firms’ forecasts that fall farthest from the consensus forecast.

Schipper and Vincent (2003) define earning quality (EQ) as ‘being related to the amount of judgment, estimation and forecasting required of preparers of the financial reports’. They state that quality decreases with the increasing incidence of reported
numbers that must be estimated by management. I therefore use an accrual-based proxy for earnings quality. The measure, \( \text{Std}\_AQI \), based on Francis, LaFond, Olsson and Schipper (2005) allows for the decomposition of firms’ EQ into quality measures relating to the firm’s ‘innate’ characteristics and also relating to the quality of the ‘discretionary’ information communicated by firm managers.

Results show that the quality of the firm’s innate accrual component is the major driver of forecast boldness. As hypothesized, I find a significant inverse relationship between forecast boldness and the quality of the innate EQ sub component. This indicates that analysts issue more bold forecasts when firms’ innate characteristics are complex and variable (low innate quality). This is likely a result of a larger demand for analysts’ advice (given a noisier earnings signal) which fuels competition among analysts to produce more accurate forecasts than their peers in order to achieve greater recognition and enhanced reputations and compensation (Stickel, 1992) or to avoid being fired as Hong et al. (2000) find that less accurate analysts are less likely to retain employment with their brokerage houses.

As hypothesized, no significant association between analysts’ bold forecasts and the discretionary component was found. However, the lack of association is likely to be due to two factors: 1) analysts’ poor understanding of the discretionary component; and 2) the diversity in the quality of firms’ discretionary component.

My tests on analysts’ ability to understand and incorporate the information contained in the discretionary component into their forecasts show that compared to their peers, analysts with greater firm specific experience incorporate more discretionary information in producing bold forecasts. This suggests that, by following a firm over a
number of years, analysts develop sharper skills in deciphering the meaning of
managements’ discretionary signals.

In relation to the diversity in quality of the discretionary component, I find that
analysts’ forecasts are bolder when managers use their discretion in earnings to provide
value relevant information to users. I interpret my results as providing indirect evidence
of analysts’ ability to interpret the value-relevant private information managers embed in
discretionary accruals (Subramanyam, 1996; Louis and Robinson, 2005). Further, my
results are consistent with analysts’ recognition of the potential for managerial
opportunism.

Overall EQ is found to be negatively related to forecast boldness. This result
implies that the innate component of accrual quality is the major driver of EQ’s
association with forecast boldness. The negative association suggests that analysts issue
bolder forecasts the lower EQ. The issue of bolder (more accurate) forecasts when EQ is
poor, suggests that analysts are satisfying investor needs by reflecting more private
information when firms have poor EQ and investors have more difficulty understanding
future earnings. This is consistent with analysts contributing positively to improve market
efficiency.

The low impact of the discretionary component on the overall EQ association
with boldness, suggests that the generally low reliability of the component lowers its
credibility especially for analysts with less firm experience (who do not appear to rely on
managements’ discretionary information).

This essay therefore contributes to the debate on whether managerial discretion
through discretionary accruals is a vehicle for their opportunism or for the transmittal of
value-relevant private information. In a large sample of firms, the discretionary component was found to be associated with bolder forecasts, albeit for more experienced analysts. This result lends support for managers’ use of discretionary accruals for information signaling. Additionally, as the sample consisted of over 16,000 firm years, it suggests that use of discretionary accruals for private information transmittal may be fairly widespread.

The paper also provides evidence on analysts’ effectiveness as capital market intermediaries. Results suggest that analysts produce bolder forecasts (reflecting more of their private information) when innate accrual quality and overall EQ are poor and therefore investors are likely to have greater difficulty predicting future earnings. Analysts therefore are responding positively to fulfill investor needs. Further results imply that when firms have informative discretionary components, analysts incorporate the discretionary information and make bolder forecasts – again displaying responsiveness to investor needs.

When the discretionary component is noisy, analysts appear to ignore the implications of firms’ poor/noisy discretionary signals when issuing bold forecasts. Thus, investors relying on analysts’ forecasts are unlikely to be fore-warned (in terms of analysts’ forecast boldness) of firms’ poor discretionary accrual quality. This of course is reminiscent of analysts’ forecasting of Enron’s earnings.

From the firm-level perspective, results suggest that herding increases with higher EQ, or alternatively, that forecasts are bolder when EQ is lower. This is driven by the strong inverse association of forecast boldness with the quality of the innate subcomponent. The result, however, is likely to emanate from two factors. First, the
reputational penalties from a large forecast error when forecasting earnings for a firm with simple operating characteristics are likely to be far worse than a large forecast error when forecasting the earnings of a more complex firm. The motivation to herd therefore should be greater for firms with good earnings quality and/or simple operating environments. Additionally, since these firms tend to be more transparent, investors are likely to demand less information on them. It is therefore rational for analysts to spend less effort to produce private information for these simple firms, and herd in order to devote more time to the more complex firms which investors are more likely to seek their advice on.

While both public opinion and the academic literature question the expertise and professionalism of the sell-side analyst this study contributes empirical evidence supportive of the sell-side analyst being an effective player in the capital market and an expert user of financial information.

This essay is organized as follows. Section 2 provides a review of related literature, Section 3 develops the hypotheses, and the research design is described in Section 4. My results are presented in Section 5, and the conclusion in Section 6.
2.0 LITERATURE REVIEW

2.1 EARNINGS

2.1.1 The Significance of the Earnings Number

The reporting and forecasting of earnings are important capital market activities that influence the flow of economic resources. These activities are inter-related, and this dissertation investigates how the quality of earnings affects the sell-side analyst’s forecasts and production of private information.

I choose to focus on earnings because of its singular importance as information in the capital market. Penman (2003, p.81) states that the market focuses on earnings as a primary summary statistic. The importance of earnings is again highlighted in Graham et al. (2005)’s survey of financial executives who report that they see earnings as the most important financial metric.

2.1.2 Perspectives for measuring the Quality of Earnings

Dechow and Schrand (2004) suggest that a high quality earnings number should do three things:

4. reflect current operating performance,
5. be a good indicator of future operating performance, and
6. accurately annuitize the intrinsic value of the company, (that is, be useful as a summary measure for assessing firm value).

This definition of high quality earnings draws several parallels to Levitt (1998)’s concept of meaningful disclosure. By giving users an indication of current operating performance, future operating performance and a measure of intrinsic value they are able
to tell investors, as Levitt (1998) says, the story of ‘where the company has been, where it is and where it will be going’.

A review of the financial reporting literature shows that there are a number of desirable bases on which earnings quality is evaluated. These bases, usually judged from a decision-usefulness approach, include attributes such as persistence (Lev, 1983), predictive ability (Lipe, 1990), smoothness (Luez et al. 2003), sustainability (Revsine et al., 1999), timeliness (Ball et al., 2000); conservatism (Basu, 1997), value relevance (Barth et al., 2001), and accrual quality (Jones, 1991).

Despite the importance of earnings, there is no universally accepted definition of what constitutes high quality earnings. Larcker and Richardson (2004) note that there are divergent views on what constitutes ‘high quality earnings’ but state that earnings quality is best defined knowing the use to which the accounting earnings will be put. There are many desirable quality dimensions (such as - persistence, predictive ability, smoothness, conservatism, value relevance, accrual quality) but earnings quality must be considered from the user’s objective.

One of the analyst’s primary objectives is the valuation of the firm, that is, the prediction and/or valuation of the firm’s future cash flows. Prior research examining the prediction of future cash flows has found that earnings better predict future operating cash flows than current operating cash flows (Dechow, Kothari and Watts (1998)). Further, Barth, Cram and Nelson (2001) find that the cash flow and the accrual components of current earnings have substantially more predictive ability for future cash flows than several lags of aggregate earnings.
Financial analysts, being engaged in earnings forecasting and firm valuation, should therefore have a significant interest in earnings and its components, accruals and cash flows. As predictive ability is enhanced by the breakdown of earnings into accruals and cash flows, the accuracy, or quality of accruals should be an important measure of earnings quality for analysts (given that accruals, rather than cash flows, contain management judgment). The quality/accuracy of accruals therefore should be significant to analysts in their forecasting and private information production decisions.

As this study examines analysts’ forecasts characteristics and private information production, a focus on the accruals component of earnings or accruals quality appears appropriate. Accruals based on the literature improve the predictive ability and contains information.

2.1.3 Judgment in Earnings – Opportunism vs Private Information releases

Generally Accepted Accounting Principles (GAAP) gives managers flexibility to use their judgment and to make estimates / accruals in determining earnings so that earnings will better reflect firm performance in the reporting period. Dechow and Dichev (2002 p. 35) states that ‘One role of accruals is to shift or adjust the recognition of cash flows over time so that the adjusted numbers (earnings) better measure firm performance.’ Accruals therefore impact the “informativeness” of earnings.

Healy and Wahlen (1999) state ‘Management's use of judgment in financial reporting has both costs and benefits.’ The costs include management’s ability to include estimates that do not reflect the firm’s underlying economics in order to ‘manage earnings’ opportunistically to further their own interests. This results in the garbling of reported earnings (Watts and Zimmerman, 1986) and ultimately in an inefficient
allocation of economic resources. On the other hand, the benefit of giving managers
discretion includes the ability for managers to communicate their private information
which adds to the informativeness of earnings and ultimately to improving resource
allocation decisions.

Badertscher, Collins and Lys (2007) refer to these two widely held views as the
‘Opportunistic’ perspective (OP) and the ‘Information’ perspective (IP). In the
opportunistic perspective, managers use discretionary accruals to enhance their personal
welfare by disguising the firm’s true economic performance. Under this view
discretionary accruals will provide misleading information to financial statement users.
On the other hand, under the information perspective, managers use discretionary
accruals to reveal private value relevant information about the firm’s future prospects.
Discretionary accruals will therefore increase the information contained in earnings.

Many studies have found that discretionary accruals are opportunistic. Most of
this evidence however has been detected in settings where the incentive for managers to
‘manage earnings’ is likely to be very strong, for example before an equity issuance
(Teoh, Welch and Wong, 1998a, 1998b), prior to management buyouts (Perry and
Williams, 1994), to meet financial analysts’ expectations (Burgstahler and Eames, 2003),
to benefit from compensation contracts (Holthausen et al, 1995) or to avoid violation of
loan covenants (DeFond and Jiambalvo, 1994)\textsuperscript{5}.

Evidence supporting the information perspective has also been found in prior
research. Subramyam (1996) concludes that on average the market attaches value to
discretionary accruals because the discretionary component increases the ability of
earnings to reflect fundamental value. Altamuro, Beatty and Weber, 2005 find that
\textsuperscript{5} See Healy and Wahlen, 1999 for a review of the earnings management literature.
revenue recognition practices of including revenue prior to completion of the earnings process on average provided value-relevant information. Louis and Robinson, 2005 also find that managers use their reporting discretion prior to stock splits to signal their private information.\(^6\)

Healy and Wahlen (1999) in their review of the earnings management literature, point out that while prior research helps investors to be aware of the likelihood of earnings management, there is not enough evidence on how pervasive earnings management (opportunistic and/or private information transfer) is.

Guay et al. (1996, p.104) conjecture that ‘[g]iven managerial discretion over accruals has survived for centuries, our prior is that the net effect of discretionary accruals in the population is to enhance earnings as a performance indicator.’ Both Guay et al.(1996) and Healy (1996)’s discussion of that paper concur that, in broad samples, both the opportunistic and information perspectives of accruals will be encountered in a cross-section of firms, as well as within one firm over time, based on the differing incentives managers face in reporting earnings.

The two views on the use of managerial discretion have different implications for the predictive usefulness of accruals and for the earnings to predict future cash flows (Badertscher et al., 2007). While there is still not enough evidence on how widespread either view is in the population, it has been noted by many studies that accruals improve the predictive ability of future cash flows (e.g. Barth, Cram and Nelson, 2001) which could suggest that ‘on average’ accruals play an informational role.

\(^6\) Other research promoting the information perspective for managerial discretion include both empirical and theoretical studies see Watts and Zimmerman, 1986; Demski 1998; and Ayra et al. 2003.
2.1.4 Accruals Quality

Dechow and Schrand (2004) state that some companies by the nature of their business will have low earnings [or accruals] quality even in the absence of intentional [opportunistic] earning management. Despite following the spirit of GAAP, companies with complex firm characteristics (such as volatile cash flows, high standard deviations in sales, long operating cycles and/or firms large in asset size with number of divisions) will have poor quality earnings due to the number of, and the difficulty of accurately making estimates to be included in earnings.

Francis, LaFond, Olsson and Schipper, 2005 (FLOS) refers to these accruals relating to the firm’s business model and operating environment as Innate accruals; as distinct from those relating to managerial discretion for opportunistic or information based reasons, which consistent with the literature is termed Discretionary accruals.

Therefore, whilst opportunistic earnings management is a source of poor accruals quality it is not the only source. Managerial errors due to the inclusion of poor estimates in earnings are another primary source of poor quality accruals, or poor innate accrual quality. Dechow and Schrand, 2004 make the point that ‘estimation errors reduce earnings persistence (because they must be corrected in future earnings) and are irrelevant for valuation. When estimates are accurate and judgments are free from managerial bias, earnings quality is high, but the opposite is true when either estimates are poor and/or judgments are opportunistic.

2.1.5 Innate vs. Discretionary Accruals

The quality of earnings is directly related to the amount and quality of management judgment and estimation included in accruals. FLOS state that ‘accruals
reflect both economic fundamentals (innate factors) and managerial choices (discretionary factors)

More complex firm characteristics make it inherently more difficult for managers to accurately estimate accruals and therefore make it unlikely for them to achieve a good mapping of their accruals into cash flows. Examples include firms with high intangible assets (e.g. research and development), firms operating in high tech industries with products with short life spans, high growth firms, or firms trading in volatile markets. Poor innate accruals therefore lead unequivocally to a reduction in the information content of earnings.

Unlike innate accruals however, the accruals relating to discretionary factors may either increase or reduce the information content of earnings, based on whether they are opportunistic or they are informative about future firm performance.

One important role played by the sell side financial analyst is to help users predict future earnings and firm value. Dechow and Schrand (2004) states that an astute analyst cannot focus on earnings alone, but must also assess the ‘quality of earnings’.

2.2 ANALYSTS

This study provides further evidence on the importance of earnings as a summary performance measure in the capital market. Additionally it sheds new light on the significance of the quality of earnings to analysts (a very important group of financial statement users) in their forecasting and private information production activities.

2.2.1 Role as Information Intermediaries

As information intermediaries, sell-side financial analysts perform a function similar to that of the external auditor. Healy and Palepu (2003, p. 23) contend that these
intermediaries exist to help investors identify stocks that are good investments and those that are lemons. Many argue that sell side analysts have failed in this regard given that analysts did not detect the ‘lemons’ in the 2002 capital market failures.

Nevertheless, in his role as an intermediary, the sell side analyst adds to firms’ information environment by producing his own private information which is input into his earnings forecasts, price targets and recommendations thus facilitating the communication of his predictions on firm value to investors (Barron, Byard and Kim, 2002).

2.2.2 Impact on the Capital Market

Gogoi (2001) reports that in October 1999 when Tyco’s analyst published a newsletter accusing the company of providing misleading disclosures about its acquisitions, investors questioned the credibility of Tyco’s disclosures and its stock price fell precipitously.

Sell side analysts’ output (forecasts, price targets and stock recommendations) are important in the capital market. Not only do they influence price (Francis and Soffer, 1997 find that analysts’ reports influence investors and hence market returns) but they also influence managers’ reporting of earnings. Graham, Harvey and Rajgopal (2005)’s survey of 402 financial executives provides evidence consistent with managers being so focused on meeting analysts’ consensus forecasts that they are willing to give up positive NPV projects.
2.2.3 Expertise

Analysts’ failure to detect irregularities in the recent financial scandals, as well as their failure to detect overvaluation in the ‘tech stock bubble’ has led many to question their independence and expertise. A CBS News (2002) report stated that:

‘...[T]en out of fifteen analysts who covered Enron kept buy ratings as late as November 8 – three weeks after initial reports of Enron’s hidden losses appeared in the Wall Street Journal and two weeks after the Securities and Exchange Commission (SEC) announced an investigation of the company...Independent analyst and president of the Center for Financial Research and Analysis suggested that many warning signs were contained in the company’s filings- such as references to “non-cash sales” and a profit of $338 million in one quarter - $264 million of which represented earnings from “unconsolidated affiliates” ’.

Prior studies have also documented that analysts’ reports, forecasts and recommendations are biased. Kothari (2001) classifies some of these biases as emanating from analysts’ incentives, from cognitive processing, from selection biases and other biases including the ‘herd behavior’ documented by Trueman (1994). Biases attributed to analyst incentives (Lim, 1998; Das et al., 1998) include evidence that analysts issue optimistic forecasts in order to gain increased access to information from management. Biases explained by cognitive-processing (Easterwood and Nut, 1999) document analysts’ overreaction to good earnings information and under reaction to bad earnings information. McNichols and O’Brien (1997) posit a selection bias where analysts are rational forecasters and truthful reporters, but report their beliefs selectively - only when they hold favorable views.

Though the arguments against analysts being effective monitors may appear persuasive, there are some mitigating factors. Many of the biases have been explained or have alternative interpretations. For example, one explanation for analysts’ optimistic
bias is explained by their desire to minimize forecast error which causes the analyst to therefore forecast the median of the earnings distribution rather than the mean. Furthermore, the optimistic bias has been declining in recent years. As analysts’ incentives are not well understood, it is not clear whether the biases demonstrated in the literature are rational or not.

There are also many studies and other evidence that would support analysts’ ability to be effective intermediaries. Studies have found that analysts provide more information in high information risk environments that are conducive to management manipulation or prone to high levels of management estimation and judgment. Barth et al. (2001) find that analysts’ coverage is increasing in firms with characteristics such as high growth, high level of intangible assets, equity issuances, and perceived mispricing. This implies that analysts’ tend to follow firms with characteristics that make valuation more difficult for investors, and hence they offer valuable intermediation services in the capital market. Barron, Byard, Kile and Reidl (2002) provide additional evidence that analysts produce additional information for firms with high intangible assets, (particularly R&D-driven high-tech manufacturers) contributing to more accurate earnings forecasts. A higher analyst following and increased effort in following these firms suggests that analysts may produce more private information when investors face more uncertainty.

2.2.4 Impact of Earnings Quality on Analysts’ Private Information Production

Several studies, both theoretical and empirical have shown that disclosure quality is inversely related to information asymmetry (Diamond and Verrecchia, 1991; Barry and Brown, 1985; Botosan, 1997). This evidence suggests that earnings quality, being a form
of disclosure, should also be inversely related to information asymmetry. Recent empirical work by Bhattacharya, Desai and Venkataraman (2007) supports this inference as it documents that poor earnings quality is manifested in the form of higher adverse selection risk and lower liquidity.

Schipper (1989) states that high levels of information asymmetry between managers and shareholders is evidence of shareholders lacking sufficient resources, incentives or access to relevant information to monitor managers’ activities. This suggests more uncertainty about firm value and therefore more opportunities for profitable private information production by analysts.

The private information incorporated into forecasts and recommendations has proven to be value relevant for the capital market (Givoly and Lakonishok, 1979). Lang and Lundholm (1996) conclude from their study that analysts use both firm-provided and privately-acquired information. This is consistent with Lys and Sohn (1990) who provide evidence that analysts’ forecasts are based on information that is partly independent across analysts and partly independent of corporate disclosures.

Barron, Byard and Kim (2002) conclude, based on their study that the idiosyncratic information contained in individual analysts’ forecasts increases immediately after earnings announcements, and that this increase is more significant as more analysts revise their forecasts. This is consistent with financial analysts using the information contained in managements’ disclosures to produce private information which is conveyed in their forecasts to investors.

This paper examines whether the quantum of analysts’ production of private information for firms is related to the firms’ earnings quality and the firms’ discretionary
accrual quality. This focus will therefore add to the debate on the analyst’s effectiveness as an information intermediary.

2.2.5 Analysts’ Herding Behavior

Trueman (1994) asserts that analysts exhibit herding behavior when they release forecasts similar to those previously released by other analysts, even where this is not justified by their information. Herding forecasts (forecast revisions which bring the analysts’ previous forecasts closer to the current consensus) are less informative and elicit smaller price responses than bold (analyst forecast revisions that diverge from the consensus) forecasts (Gleason and Lee, 2003). Clement and Tse (2005) find that herding forecasts are less accurate than bold forecasts. These studies are consistent with herding behavior potentially lengthening the time period that private information is assimilated in the market and reflected in security prices.

It is possible that analysts following the same firm may have similar information and so produce similar forecasts. These forecasts could be incorrectly classified as herding forecasts. Welch (2000) in a study of analysts’ recommendations finds evidence that herding towards the consensus does not appear to be information driven as analysts herding towards the consensus is no stronger when the consensus is a good predictor (ex post) of future stock return.

Devenow and Welch (1996)’s discussion of rational herding in financial markets present models which predict herding in which rational agents all act alike without any countervailing forces. Examples include the principal-agent model where in order to preserve or gain a reputation when markets are imperfectly informed, agents may prefer
to ‘hide in the herd’ to avoid evaluation, or else may prefer to ‘ride the herd’ in order to prove their quality.

The growing literature on herding has attributed herding behavior to a number of factors. The theoretical literature mainly attributes herding to concerns about reputation and relative performance evaluation. Scharfstein and Stein (1990) conclude that herding may result from analysts’ attempts to enhance their reputations. Trueman (1994) refine this by stating that analysts’ tendency to herd is an attempt to enhance their reputations for high forecasting ability. Kim and Zapatero (2010) suggest that relative performance evaluation plays an important role in analysts’ herding decisions. They document that herding can arise when the penalty for under-performing the other analysts is very high.

Empirical studies have found other factors that contribute to herding. Kim and Pantzalis (2003) find that complexity, (proxied by global or industrial diversification) exacerbates the analyst’s tendency to herding because it makes forecasting more challenging. This is in line with Olsen (1996)’s finding that suggests that herding exists and increases with the level of earnings unpredictability (as per Value Line’s earnings predictability index).

Trueman (1994)’s claim that analysts self confidence plays a role in the issue of bold forecasts is supported by Hong, Kubik and Solomon (2000)’s finding that less experienced analysts are more likely to issue herding forecasts; and by Clement and Tse (2005)’s results which show that the likelihood of analysts’ issuing a ‘bold’ forecast is increasing in their prior accuracy, brokerage size and experience.

Finally some studies show that herding increases as the competitiveness of the forecasting environment, or forecasting accuracy increases. For example, Stickel (1990)
using stock market data finds that earnings herding intensifies as the number of estimates close to the consensus increases and the quality of one’s prior forecast increases; and Cote and Sanders (1995) find that herding increases with the credibility of the consensus.

While the prior literature relates herding to several factors, none focus on the primary ‘raw material’ used in forecasting – earnings, its accrual component and its quality. The quality of earnings is fundamental to setting the tone of the forecasting environment and can affect the factors that have been shown in the prior literature to be associated with analysts’ herding behavior. Earnings quality affects several key factors related to the competitiveness of analysts’ forecasting environment. Firms with higher EQ have higher analysts following which impacts the analyst’s reputational concerns; higher EQ facilitates analysts’ forecast accuracy and hence should lead to more credible consensus forecasts and lower demand for analysts’ advice. This therefore increases analysts’ incentives to herd.

A study of the relationship between analysts herding and earnings quality therefore should significantly increase our understanding of analysts’ herding behavior.

2.2.6 Earnings Quality’s association with Analysts’ Bold Forecasts

Prior literature suggests that analysts have incentives to issue accurate forecasts. Stickel (1992) shows that the highly recognized Institutional Investor All Star Analysts issue more accurate forecasts than their peers (Stickel, 1992). Mikhail et al. (1997) find that more accurate analysts are less likely to ‘turn over’, that is, to change brokerage houses or to quit forecasting than their less accurate peers. Hong, Kubrik and Solomon (2000) also provide evidence of greater career concerns for less experienced analysts.
They find that less experienced analysts are more likely to be terminated for inaccurate forecasts.

Bold forecasts (forecasts that deviate more from the consensus) have been found to elicit more market reaction (Gleason and Lee, 2003) which Clement and Lee (2005) attribute to their higher accuracy. Bold forecasts benefit from larger releases of analysts’ private information relative to herding forecasts. Theories of analyst herding based on reputational concerns answer the question as to what motivates analysts to herd when they have incentives to issue bold forecasts and the market responds more to bold forecasts.

Hirshleifer and Teoh (2003) state that the importance of relative evaluation is consistent with reputational models of herding. Trueman (1994)’s reputational herding model implies that analysts’ herding behavior is associated with reputational concerns, and that analysts with greater ability will be less influenced by previous forecasts than will those of weaker analysts. Trueman attributes forecast boldness to analysts’ confidence.

While previous literature is focused on analysts’ personal characteristics as factors that affect their confidence (e.g., experience, prior accuracy and ability) I investigate how the clarity or opaqueness of the firm’s earnings quality affects analysts’ forecast boldness. Barker and Shahed (2008) find that EQ is a major component of analysts’ private information and therefore it is likely that analysts’ forecast boldness and herding behavior are also associated with the quality of earnings.
3.0 HYPOTHESIS DEVELOPMENT

3.1.0 Earnings Quality and Analysts’ Forecast Boldness

Prior research documents several benefits associated with analysts’ production of accurate forecasts. Included amongst the advantages are the achievement of greater recognition, improved reputation, higher compensation and career advancement (Stickel, 1992; Michael et al., 2000; Hong et al. 2000). Analysts generate private information in order to improve the accuracy of their forecasts and, hence, the value of their investment advice to investors. As private information improves forecast accuracy, by reflecting more of their private information in their forecasts analysts should improve their accuracy as well as their chances of being recognized as a highly skilled analyst. This is consistent with Clement and Tse (2005)’s finding that bold forecasts are more accurate and contain more of the analyst’s private information.

However, analysts’ appear to reach an unusual amount of consensus in their estimates of future earnings relative to the predictability of earnings (DeBondt and Forbes, 1999). The theoretical literature attributes this clustering of forecasts around the consensus to analysts’ reputational concerns, career anxiety and a lack of self-confidence in their forecasting ability.

This study looks at how EQ and its components affect the analyst’s herding behavior by examining the impact of EQ on the demand for private information, and on analysts’ relative performance evaluation.
3.1.1 **Earnings Quality, clarity of the Earnings Signal and the demand for Analysts’ Investment Advice**

Barker and Shahed (2008) find that earnings and earnings quality are important inputs into the financial analyst’s reports. This is consistent with studies which find that earnings and its accrual and cash flow components are valuable predictors of future earnings (Barth, Cram and Nelson, 2000).

Richardson (2000) documents a systematic negative relationship between the magnitude of information asymmetry and the quality of earnings (proxied by the level of earnings management). That is, information asymmetry is higher the lower the earnings quality. This is in line with theoretical studies that document an inverse relationship between disclosure quality and information asymmetry (Diamond and Verrecchia, 1991).

The inverse association between disclosure quality and information asymmetry implies that firms with high quality earnings provide users with a clearer signal of future earnings performance than firms with poor earning quality. This is consistent with empirical studies such as Bhattacharya, et al. (2007)’s finding that investors have more difficulty valuing firms with low earnings quality. This implies that users’ demand for analysts’ investment advice will be lower/ (higher) for firms with high/ (low) earnings quality.

The quality of earnings, and its components have an important relationship with the strength of the earnings signal and the accuracy of the consensus forecast. The differences in the characteristics of the innate and discretionary components affect the quality of analysts’ public information and hence the clarity of the earnings signal. Both
components must be considered in accounting for EQ’s overall association with analysts’
information and forecasting behavior.

FLOS (2005) find that the information contained in these two major accrual subcomponents differ in precision and reliability. While the innate component is related to more objective operating factors, the discretionary component contains information from managements’ subjective choices – which may be value relevant (i.e. providing information relating to future performance) or noisy (accruals made to further managers’ opportunistic objectives as well as corrections of prior estimation errors). FLOS (2005) find that the discretionary component is less reliable and more variable than the innate component. This suggests that, on average, the earnings signal emanating from the innate component should be stronger than that from the discretionary component.

3.1.2 The association of the Quality of the Innate Accrual component with Analysts’ Forecast Boldness

The innate component reflects the variability and complexity of the firm’s operations. The quality of the firm’s innate component varies inversely with the variability and complexity of the firm’s business model and operations. The factors affecting complexity are related to operating characteristics and include variables such as the firm’s operating cycle, the variability of sales and cash flows, firm size and the number of recent losses reported by the firm. These factors can be objectively and precisely measured by analysts and are likely to be inputs in their proprietary models used to generate estimates of firms’ future earnings.
The poorer the innate accrual quality (high variability and complexity of firm operations) the weaker the signal of future earnings emitted by the innate accrual component. This is consistent with findings in Essay 1 that lower innate accrual quality is associated with higher forecast errors the dispersion.

The weaker signal of future earnings suggests that users’ reliance on analysts for investment advice will be greater, thus providing analysts with more incentive to produce private information. Producing greater amounts of private information should give analysts a better understanding of firm performance and hence more confidence in the accuracy of their private information. Analysts therefore should be more likely to issue bolder forecasts in order to outperform their peers and enhance their reputations in order to increase their commission earnings.

Further as firm complexity and variability (reflected by higher values of the innate component) reduce the clarity of the earnings signal, there will be wider variability in analysts’ forecasts and a less accurate consensus forecast. This suggests that when innate accrual quality is low, the reputational penalties of producing a bold forecast that ‘misses’ the actual earnings are less severe (relative to when innate accrual quality is high) as many of the other analysts will also ‘miss the mark’.

Given a greater potential to earn commission income, a richer forecasting environment in which to demonstrate their ability, along with lower reputational penalties if they prove to be incorrect, analysts are likely to produce more private information and issue bolder forecasts for firms with low quality innate components.

I therefore state my hypothesis:

**H1: The likelihood of bold forecasts is inversely associated with the quality of**
the innate accrual component.

3.1.3 The association of the Discretionary Earnings component with Analysts’ Forecast Boldness

The discretionary component of accrual quality relates the variability in the earnings signal to management’s discretionary choices relating to information used in the earnings determination process. As the discretionary component may be used by management for opportunistic reasons, it is often associated with ‘opaque’ accounting or a lack of transparency in financial reporting.

Guay et al. (1996) in their discussion of management’s discretion in earnings state that the discretionary component may itself consist of up to three subcomponents. The first, a ‘performance’ subcomponent that adds value relevant information to earnings, and two other sub-components ‘opportunism’ and ‘noise’ that reduce the reliability of the information in earnings.

Guay et al. (1996) and Healy (1996) state that a broad sample of firms covering a long time period will include firms with informative discretionary earnings components and others with opportunistic (or manipulative) discretionary components. Francis et al. (2005) provide evidence of this heterogeneity (firms with both informative and noisy discretionary components) with their study’s broad sample of firms. Healy (1996) further states that a firm may even change over time from having an informative discretionary component to having a manipulative one, or vice versa, depending on the incentives faced by management.
Healy concludes that the overall observed effect for a given sample will be the weighted average of the separate effects. Thus in a sample of firms the weighted average discretionary component of accrual quality may reflect value relevant information, or may be noisy.

If on average the discretionary component provides value relevant information, then analysts who understand managements’ signals should receive a stronger signal of future earnings and should be more confident in issuing bolder forecasts to capitalize on their competitive advantage.

However the discretionary component may on average be noisy. That is, the majority of firm managers may use manipulative discretionary accruals to garble the earnings signal. Analysts will, therefore, have difficulty comprehending the discretionary information which being misleading, will not improve the accuracy of their forecasts. The low reliability, precision and complexity of the discretionary component may even cause analysts to ignore discretionary information in their forecasting (Plumlee, 2003).

Analysts’ reaction to the discretionary component, therefore, may be subdued by both the low reliability of the information, and by the low level of skill analysts have been shown to have in identifying manipulative accruals as well as in understanding the persistence of accruals (Sloan, 1996; Xie, 2003).

I hypothesize that:

**H2 (1): The likelihood of bold forecasts is not associated with the quality of the discretionary accrual component.**
3.1.3.1 Discretionary Component of Accrual Quality and Analysts with high Firm Specific Experience

The skill to decipher whether a firm’s discretionary component of accrual quality contains value relevant information or whether it is noisy is likely to be developed over time as an analyst follows a particular firm and becomes more familiar with managerial objectives, the firm’s reporting practices, and its corporate governance policies.

For the average analyst, synthesizing all this information may be a difficult task. The literature contains many studies that document analysts’ poor understanding and use of the information in accruals (Bradshaw, Richardson and Sloan, 2001; Sloan, 1996). More experienced analysts should therefore have a competitive (knowledge) advantage over their peers with less firm specific experienced.

Trueman (1994, p. 107) predicts that herding will decline with analysts’ firm-specific experience. Hong et al. (2000)’s empirical findings imply that the pressure to build reputation is strongest for analysts whose ability is not yet ascertained by the market. Hong et al. (2000) also finds that more experienced analysts have higher job security and the risk of termination for poor forecast accuracy is higher for less experienced analysts than for their more experienced counterparts. This suggests that analysts with less firm specific experience (having not yet established a reputation for accuracy) should be less likely than their more experienced peers to issue bold forecasts since an inaccurate bold forecast is more likely to more negatively impact their reputations and also is more likely to cost them their jobs.

On the other hand analysts with more firm specific experience having less career concerns and having devoted years to the research and analysis of the firm’s performance
and managers’ discretionary signaling should have greater confidence in issuing bolder forecasts incorporating managements’ discretionary information.

**H2 (2): For analysts with greater firm specific experience, the likelihood of bold forecasts is positively associated with the discretionary component of accrual quality.**

3.1.4  **Earnings Quality’s association with Analysts’ Bold Forecasting**

Earnings quality’s overall association with Analysts’ Forecast Boldness will be jointly determined by the association of its sub-components– (the innate and discretionary components) with forecast boldness. Each subcomponent emits a distinct signal of information relevant to forecasting earnings. The innate component provides information about the firm’s operating environment, while the discretionary component supplies information about accounting policy choices and about the quality of managements’ estimates and judgments included in earnings.

As detailed in hypothesis 1, I expect that the innate component will have an inverse association with forecast boldness; while I expect that the discretionary component will not be associated with forecast boldness for reasons explained in hypothesis 2. FLOS (2005) find that the innate component is larger and more reliable than the discretionary component, I therefore expect that overall EQ will be driven by the innate component and hence expect an inverse relationship between forecast boldness and earnings quality.

An inverse association, producing bolder forecasts when EQ is low, is consistent with the very competitive nature of the forecasting environment and analysts’ incentive to
be evaluated as ‘smart’ in order to attract higher client commissions and career advancement. Analysts are more likely to produce more private information to make bold forecasts when overall EQ is low so that they can better differentiate themselves from their peers, enhance their reputations and increase their remuneration. Further, the reputational penalties for producing a bold forecast if it proves incorrect should tend to be small due to the lower accuracy and higher dispersion associated with poor quality earnings. The benefits therefore of producing bold forecasts should out-weigh the penalties and analysts should issue bolder forecasts when EQ is low.

I hypothesize that:

**H3: The frequency of bold forecasts is inversely associated with the quality of earnings.**
4.0 RESEARCH DESIGN

This section describes the variable measurement (4.1), empirical models (4.2), sample selection (4.3) and descriptive statistics (4.4) used in testing my hypotheses, and concludes with univariate results (4.5) of the tests performed.

4.1 VARIABLE MEASUREMENT

4.1.1 Dependent Variables

Herding is measured both at the individual analyst’s forecast type (bold or herding) as well as at the firm level. At the individual forecast level, tests will show how EQ is related to the boldness of the analyst’s revised forecast. Consistent with prior research, boldness is estimated as the deviation of the analyst’s forecast from the existing consensus forecast. Bolder forecasts (which are assumed to contain more of the analyst’s private information) deviate more from the consensus forecast than herding forecasts (which contain less private information).

The ConDis proxy estimates forecast boldness at the individual forecast level as the absolute value of the deviation of analysts’ forecasts from the existing consensus forecast.

At the firm level, boldness is evaluated based on the distributional characteristics of the firm’s earnings forecasts. The DHI proxy adopted from prior research assumes that analysts’ forecasts are normally distributed and measure the degree of boldness by comparing the actual number of forecasts outside of the 95% confidence interval with the expected number based on a normal distribution (Mensah and Yang, 2008). Tests of
boldness at the firm level show how a firms’ EQ affects the boldness of its analyst’s forecasts.

**Measures of Forecast Boldness/Herding at the Analyst Forecast Level**

**Proxy for Herding - ConDis**

This proxy is based on a measure of forecast boldness used in Clement and Tse (2005). It proxies bold forecasts by the deviation (in absolute terms) of the analyst’s revised forecast ($F_{i,j,t}$) from the consensus forecast immediately preceding the release of the analyst’s revised forecast ($F_{cur}$). Longer distances, or larger movements away from the existing consensus, show increased forecast “boldness” while relatively smaller movements are adjudged “herding” forecasts.

$$ConDis = | F_{i,j,t} - F_{cur -i,j,t} |$$

**Proxy for Herding - YtdDis**

As an alternate proxy for forecast boldness I calculate $YtdDis$. This measure adopted from Hong, Kubik and Solomon (2000) estimates boldness as the deviation (in absolute terms) of analyst $i$’s most recent forecast in the sample period from the consensus forecast at the end of the period (based on the latest forecasts of all the other analysts following the stock $j$ in year $t$ except analyt $i$).

$$YtdDis = | F_{i,j,t} - F_{bar -i,j,t} |$$

Both $ConDis$ and $YtdDis$ measure boldness by the deviation of analysts’ revised forecasts from some consensus forecast. The $ConDis$ proxy however uses the deviation
from the consensus existing immediately before the issue of the analyst’s revised forecast. This proxy therefore takes account of the order in which the forecasts were released which according to Trueman (1994) is appropriate in measuring herding.

Given \textit{ConDis}’ relative advantage over \textit{YtdDis} and the fact that tests of hypotheses using either of these proxies as the dependent variable give similar results, I only report in the Tables the results using the \textit{ConDis} proxy.

**Measures of Forecast Boldness/Herding at the Firm Level**

**Proxy for Herding (DHI)**

This proxy for herding behavior \textit{DHI} is adopted from Mensah and Yang (2008) which is based on Olsen (1996).

\textit{DHI} – This measure of herding is based on the premise that analysts’ forecasts of firms’ earnings should follow a normal distribution. Thus, if herding occurs the distribution will be more ‘tightly’ distributed with fewer forecasts in the tails of the distribution.

\[
DHI = 1.0 - \left[ \frac{\text{Lower 95\% CI}}{\# \text{Forecasts}} \leq \# \text{Analysts} \leq \frac{\text{Upper 95\% CI}}{\# \text{Analysts}} \right]
\]

where:

\textit{Lower 95\% CI (confidence interval)} = Mean forecast – 1.98 (standard error of the mean)

\textit{Upper 95\% CI (confidence interval)} = Mean forecast + 1.98 (standard error of the mean).

\textit{DHI the actual} percentage of forecasts that fall outside the 95\% confidence interval (of the mean forecast for the sample period) therefore provides a measure of
analysts’ tendency to issue bold forecasts and an inverse measure of analysts’ herding behavior. The maximum value of 1 indicates the extreme and unlikely case where 100% of the forecasts fall outside the 95% CI reflecting very bold forecasting or alternatively, a very low probability of herding. Conversely, the minimum value of 0 indicates that 100% of the forecasts fall within the 95% interval suggesting a high probability of herding and a low probability of bold forecasting.

4.1.2 Independent Variables

Earnings Quality Proxy

The ability to predict next period’s earnings is likely to be greatly enhanced by both the accuracy of accruals as well as by the consistency of firms’ accrual quality. The accuracy of accruals and their reliability from period to period should therefore be important to analysts when relying on them to forecast earnings. My proxy for earnings quality, $\text{Std}_AQI$, reflects both accrual accuracy and consistency.

The $\text{Std}_AQI$ measure

The earnings quality measure, $\text{Std}_AQI^7$, is based on Dechow and Dichev’s (2002) measure of the quality of working capital accruals and earnings, modified by the inclusion of additional variables (i.e. $PPE$ to account for non current accruals and $\Delta Rev$ to control for volatility) as suggested in McNichols’ (2002) discussion of the model. $\text{Std}_AQI$ is the standard deviation of firm $j$’s residuals (in the five years $t$ to $t-4$) from

---

$^7$This proxy is also used by Francis, LaFond, Olsson and Schipper (2005) as their measure of accruals quality ($AQ$) measure.
annual cross-sectional regressions relating current accruals to cash flows (see equation 1 below):

\[
TCA_{j,t} = \phi_0 + \varphi_{1,j} CFO_{j,t-1} + \varphi_{2,j} CFO_{j,t-2} + \varphi_{3,j} \Delta Rev + \varphi_{5,j} PPE + \nu_{j,t} \tag{1}
\]

where:

Firm \( j \)'s total current accruals in year \( t \), \( TCA_{j,t} \) = \( (\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}) \);

\( \Delta CA_{j,t} \) is the change in firm \( j \)'s current assets (Compustat #4) between year \( t-1 \) and year \( t \) scaled by average total assets; \( \Delta CL_{j,t} \) is the change in firm \( j \)'s current liabilities (Compustat #5) between year \( t \) and year \( t-1 \) scaled by average total assets; \( \Delta Cash_{j,t} \) is the change in firm \( j \)'s cash resources (Compustat #1) between year \( t \) and year \( t-1 \) scaled by average total assets; and \( \Delta STDEBT_{j,t} \) = Firm \( j \)'s change in debt in current liabilities (Compustat #34) between year \( t \) and year \( t-1 \). Firm \( j \)'s cash flow from operations in year \( t \), \( CFO_{j,t} \) = Compustat data item #308. \( \Delta Rev \) = firm \( j \)'s change in revenue (Compustat #12) between year \( t \) and year \( t-1 \) and PPE is firm \( j \)'s gross value of property, plant and equipment (Compustat #7) in year \( t \).

The residual, \( \nu_{j,t} \), represents current accruals that are not associated with cash flows in either the current year, previous year or in the next financial year. These unmatched accruals are assumed to be due to managements’ error in the estimates and judgments incorporated into earnings. The larger the residual, the higher the errors included in earnings.

Values of \( Std_{AQI_j} \) \( t = \sigma(\nu_{j,t}) \) (the five year standard deviation of the residual) are calculated for all firms with available data in the sample. \( Std_{AQI} \) is a proxy of the variability of the firm’s earnings signal.
To be included in the tests of my hypotheses, each firm-year observation has to have data on $Std\_AQI$ and the necessary dependent variable measure. As $\sigma(\upsilon_j)t$ is based on five annual residuals, the sample is restricted to firms with at least 7 years of data (as Eq. (1) includes both lead and lag cash flows).

**Interpretation of the $Std\_AQI$ measure**

Higher values of $Std\_AQI$ reflect greater variability in accruals quality or poorer earnings quality, as future accruals (and earnings) will be more difficult to predict. As the study considers the quality of earnings from the perspective of the analyst’s forecasting decisions, it is the consistency of the residuals rather than their size that determines predictive ability and hence ‘quality’. Even where residuals are consistently large (but have a small standard deviation) accruals quality will be relatively high. Despite a poor mapping, a small standard deviation of residuals will allow analysts to better predict future earnings due to the relative consistency of accruals quality, thus facilitating analysts’ prediction of accruals and earnings. On the other hand, larger magnitudes of $Std\_AQI$ signify greater uncertainty (less predictability) and hence increase the difficulty for analysts in forecasting accruals, future earnings and firm value.

**Segregating Accruals into Innate ($InnAQ$) and Discretionary ($DAQ$) Accrual Quality Components**

An added benefit of this accruals/earnings quality proxy is that it can be decomposed into measures of two earnings quality subcomponents. The first, the quality of the innate accrual component ($InnAQ$), that is, the quality of the accruals driven by the
firm’s business model and operating environment; while the second reflects the quality of discretionary accruals component \((DAQ)\), or the quality of managers’ discretion reflected in accruals.

To derive the quality metrics for these components, annual regressions of \(\text{Std}_AQI\) are run on the innate factors identified by Dechow and Dichev (2002) – firm size \((\text{Mean}_\text{size})\), standard deviation of cash flows from operations \((\text{Std}_\text{CFO})\), standard deviation of sales revenue \((\text{Std}_\text{Rev})\), length of operating cycle \((\text{LOOP})\) and the incidence of negative earnings realizations \((\text{Losses})\). The predicted value from each regression is used to estimate the firm’s innate accrual quality while the error serves as an estimate of discretionary accrual quality (Francis et al., 2005).

\[
\text{Std}_AQI = \delta + \delta \text{Mean}_\text{size} + \delta \text{Std}_\text{CFO} + \delta \text{Std}_\text{Rev} + \delta \text{LOOP} + \delta \text{Losses} + \epsilon \quad (2)
\]

Hence the firm’s earnings quality measure, \(\text{Std}_AQI\), is segregated into two components. One component (the fitted values from equation 2) that relates the variability in accruals quality \((\text{Std}_AQI)\) to the firm’s inherent operating environment, gives a measure of the firm’s innate accrual quality \((\text{InnAQ})\). The other component (the residual from equation 2) variability in accrual quality that is unrelated to firm characteristics is assumed to be the result of managements’ discretion- and therefore a proxy for the quality of the discretionary accruals component \((DAQ)\).

\text{InnAQ}

Following FLOS, I use \(\text{InnAQ}\), the fitted value of equation (2), as a proxy of the quality of the firm’s innate accrual component. \(\text{InnAQ}\) reflects the amount of accrual and cash flow ‘miss-match’ (variability in \(\text{Std}_AQI\)) that is predicted by the complexity of the firm’s operating environment. The more complex the firm, (and therefore the larger the
amount of management estimation and judgment required in calculating the earnings number), the higher the value of InnAQ will be. As larger values of InnAQ reflect lower innate accrual quality, InnAQ is an inverse measure of innate accrual quality.

**DAO and absDAQ**

*DAO* measured as the residual of equation (2), represents the variability in accrual quality accorded to management discretion (or alternatively it is the difference between actual (*Std_AQi*) and predicted variability (*InnAQ*). Positive values of *DAO* indicate that managers’ discretionary accruals increased the variability of *Std_AQi* earnings quality, while negative values indicate the opposite—managers’ discretionary accruals reduced the variability of *Std_AQi*.

The discretionary accrual component proxies for the deviation in analysts’ expectations of actual accrual variability from predicted variability based on innate firm characteristics. As analysts likely face the same difficulty in understanding deviations (whether positive or negative) from expected variability, I use the magnitude, that is the absolute value, of the discretionary component, *absDAQ* as a measure of the size of the discretionary accrual component. *absDAQ* therefore reflects the amount of variability in accrual quality due to managements’ discretion and serves as my proxy for the quality of the firm’s discretionary accrual earnings component.

### 4.2 Empirical Models

Empirical models are estimated with OLS regressions and include fixed effects for year and industry to control for cross sectional correlation in the panel data. Additionally, standard errors are robust to clustering by firm and year.
4.2.1 Empirical Model for Testing Hypotheses 1 & 2(1)

Model 1 - forecast level

\[ ConDis_{i,t} = \alpha + \lambda yr + \delta ind + \beta_1 InnAQ + \beta_2 absDAQ* + \beta_3 Accur + \beta_4 AFSExp + \beta_5 Brokersize + \beta_6 FCfreq + \beta_7 Horizn + \beta_8 No\_Firms + \beta_9 DaysElaps + \beta_9 \log(TAs) + \beta_{10} Following + \beta_{11} Eqiss + \varepsilon \]  

(3)

* the model is estimated with both the absolute value and the signed value of discretionary accruals

Test:

If: \( \beta_2 \) InnAQ is positive this implies that bold forecasting / (herding behavior) is higher / (lower) for firms with lower earnings quality. A negative coefficient implies the opposite. The hypothesis predicts the coefficient is positive.

\( \beta_2 \) absDAQ is positive this indicates that firms with larger discretionary components have bolder forecasts; or alternatively, firms with smaller discretionary components have a greater frequency of herding forecasts.

\( \beta_2 \) DAQ is negative this indicates that analysts’ issue bolder forecasts / (more herding forecasts) for firms whose managers use their discretion to reduce / (increase) the variability of earnings.

Model 2 – firm level

\[ DHI_{i,t} = \alpha + \lambda yr + \delta ind + \beta_1 InnAQ + \beta_2 absDAQ* + \beta_3 Me\_Accur + \beta_4 Following + \beta_5 Me\_AFSExp + \beta_6 Me\_No\_Firms + \beta_7 Brksize + \beta_8 Me\_Size + \beta_9 EqIss + \varepsilon \]  

(4)
Predicted relationships for variables of interest:

\textit{H1&2(1)}

The coefficient on $\beta_1 (InnAQ)$ is expected to be positive and significant reflecting more bold forecasts when InnAQ is higher (poorer EQ). Increases in InnAQ (i.e. reductions in the quality of the innate accrual component) reflect greater firm complexity. Complexity leads to more estimation in earnings and thus produces a noisier signal of firm performance. With less reliable information investors are likely to demand more investment advice from analysts. A positive coefficient suggests that analysts reveal more of their private information when EQ is poor which is consistent with analysts competing to produce accurate forecasts in order to enhance their reputation and career goals.

The discretionary component is not well understood by investors (Xie, 2001) and therefore their reliance on analysts’ advice is likely to be higher for firms with large discretionary components of accrual quality, giving analysts greater incentive to produce bold forecasts to gain more visibility relative to their peers with the objective of attracting more business.

Theory supports both a positive and/or a negative association between forecast boldness and the quality of the discretionary accrual component of earnings. If the discretionary accrual component provides value relevant information (Subramanyam, 1996) then forecast boldness should be higher (positively related) the larger the size of the firms’ discretionary accrual component- and therefore the coefficient on $absDAQ$ will be positive. However, if the majority of firms have discretionary accrual components that are noisy then the relationship with forecast boldness will be inverse and the coefficient on $\beta_2 (absDAQ)$ will be negative.
CONTROL VARIABLES

I control for variables which have been shown in the prior literature to be associated with forecast boldness or analysts’ herding behavior. Clement and Tse (2005) show that forecast boldness is associated with analysts’ prior accuracy ($Accur$), analysts’ forecast frequency ($FcFreq$), forecast horizon ($Horizn$), analyst experience ($AFSExp$), the size of the brokerage house employing the analyst ($Brokersize$), the number of days elapsed since the analysts previous forecast ($DaysElaps$) and the number of firms followed by the analyst ($No_Firms$). I control for these variables as well as for the number of analysts following the firm ($Following$) and firms’ equity issuance ($Eqiss$), as these variables are likely to affect the firm’s information environment and the analyst’s competitive environment and could lead to biased results if not included in the model.

At the firm level, controls include the mean size of the firm ($Mean\_Size$), the number of analysts following the firm ($Following$), the mean accuracy of the analysts following the firm ($Me\_Accur$), whether the firm had an equity issue in the forecast year ($EqIss$), the mean number of firms followed by the analysts in the forecast year ($Me\_No\_Firms$), the mean size of the brokerage houses the analysts following the firm are employed to ($Mean\_Brksize$), and the mean firm specific experience of the analysts following the firm in the forecast year ($Me\_FSExp$).

4.2.2 Empirical Model for Testing Hypothesis 2(2)

Hypothesis 2(2) predicts that analysts with more firm specific experience will produce bolder forecasts the larger the discretionary component. This hypothesis can be more directly tested at the forecast level as analysts with more firm experience can be segregated and their forecasts can be identified and their boldness directly measured. (At
the firm level, the test is likely to be very low power as only the mean firm experience can be identified). Tests of the hypothesis at the forecast level only are performed using the model below:

**Model (forecast level)**

\[ \text{ConDis} = \beta_0 + \beta_1 \text{InnAQ} + \beta_2 \text{absDAQ} + \beta_3 \text{Accur} + \beta_4 \text{AFSExp} + \beta_5 \text{Brokersize} \\
+ \beta_6 \text{FCFreq} + \beta_7 \text{Horizon} + \beta_8 \text{No_Firms} + \beta_9 \text{DaysElaps} + \beta_{10} \text{lgTAs} \\
+ \beta_{11} \text{Following} + B_{12} \text{Eqiss} + \beta_{13} \text{HiFSex} + \beta_{14} \text{HFSxabsDAQ} + \epsilon \]  

(5)

**Tests of H2(2)**

Two additional variables are added to the model:

- **HiFSex** a dummy variable set to 1 when analysts have 3 or more years of firm specific experience and 0 otherwise; and
- **HFSxabsDAQ** an interactive variable between **HiFSex** and **absDAQ**. This variable gives the differential effect of a one unit change in the discretionary component on forecast boldness between experienced and inexperienced analysts.

**Prediction**

H2(2) predicts that the sum of coefficients \((\beta_2 + \beta_{14})\) will be positive.

4.2.3 **Empirical Model for Testing Hypothesis 3**

Hypothesis 3 (H3) the frequency of bold forecasts is negatively associated with earnings quality. The following models are employed to test the hypothesis:

**H3**

**Model 1- at the forecast level**

\[ \text{ConDis}_{i,t} = \alpha + \lambda \text{yr} + \delta \text{ind} + \beta_1 \text{Std_AQI} + \beta_2 \text{Accur} + \beta_3 \text{AFSExp} + \beta_4 \text{Brokersize} \]
\[ +\beta_5 \text{FCfreq} + \beta_6 \text{Horizon} + \beta_7 \text{No\_Firms} + \beta_8 \text{DaysElaps} + \beta_9 \text{lgTAs} \]
\[ + \beta_{10} \text{Following} + \beta_{11} \text{Eqiss} + \varepsilon \]  \hspace{1cm} (6)

Model 2 – at the firm level

\[ DHI_t = \alpha + \lambda_{yr} + \delta_{\text{ind}} + \beta_1 \text{Std\_AQI} + \beta_2 \text{Me\_Accur} + \beta_3 \text{Following} + \beta_4 \text{Me\_AFSExp} + \]
\[ \beta_5 \text{Me\_No\_Firms} + \beta_6 \text{Me\_Brksize} + \beta_7 \text{Me\_Size} + \beta_8 \text{EqIss} + \varepsilon \]  \hspace{1cm} (7)

Timing of Variable measurement

Both ConDis and DHI use analysts’ forecasts of annual earnings (from I/B/E/S) made after the release of the firm’s prior year \( t-1 \) annual financial statements but before the issue of the 1st quarters’ earnings announcement for year \( t \). Earnings quality variables (\textit{Std\_AQI}) and other independent variables are based on Compustat’s financial information at year end \( t-1 \).

Test:

If: \( \beta_1 \text{Std\_AQI} \) is positive this implies that the frequency of bold forecasts is higher for firms with lower earnings quality. Hypothesis three predicts that the coefficient is positive.

4.3. **STATISTICAL TESTS**

The study uses OLS regression analysis to test the hypotheses. The dataset (panel data) consists of analysts’ forecasts for a number of firms over a number of years. It is therefore likely that the variables are both cross-sectionally and serially correlated. As
such regression errors are unlikely to be independent and can create misspecified test statistics (Bernard, 1987).

To correct for both cross-sectional and time-series dependence I use two-way cluster (clustering by firm and by year) robust standard errors which the econometric literature shows provides a suitable control for both patterns of dependence (Petersen, 2008; Gow et al., 2009). For robustness I also include fixed effects year and industry dummies as the dataset covers 14 years and 40 industries.

4.4 SAMPLE SELECTION

All tests are based on I/B/E/S forecasts of annual earnings of year $t$ issued after the release of the prior years’ annual financial statements but before the firm’s first quarter earnings are announced (See Figure 1 for timeline used for variable measurement). These restrictions increase the likelihood that analysts relied on the firm’s most recent annual report to produce their forecasts, that is, the financial statement information for year end $t-1$ when producing their forecasts of year $t$’s earnings.

An added benefit of using forecasts made early in the financial year as per Barron, Byard and Kim, 2002, is that analysts are focused on forecasting core earnings (rather than any management manipulations of earnings). Finally, by limiting the sample to forecasts made in this relatively short period (a mean of 51 days), I avoid including stale forecasts (Brown and Kim (1991)) in the analysis.

The sample data includes all analysts’ annual forecasts in the period 1992 – 2005 with the required earnings announcement dates for the prior year’s fourth quarter and the current year’s first quarter; as well as the required annual financial data from Compustat.
for control variables and earnings quality measures (7 years of data are required to compute the annual EQ proxies).

The final samples are comprised of, for the ConDis regression 16,377 annual forecasts; for the YtdDis regression 15,011 forecasts; and for the DHI regression 10,472 forecasts.

4.5 DESCRIPTIVE STATISTICS

Table 1 reports descriptive information about the variables. Panels (1) and (2) give the descriptive statistics of the variables used in the regressions with the dependent variables ConDis and DHI respectively; while Panel (3) gives the descriptive statistics on the sample firms used in this study to derive the earnings quality variables and compares them to the statistics in the FLOS (2005) sample.

The mean and median values of Std_AQI in Sample A (at the forecast level) are 0.04 and 0.03 respectively which are the same as reported in FLOS (2005)’s sample statistics. Sample B at the firm level however has slightly higher mean and median values of Std_AQI which implies that the average EQ of these firms is a little lower than those included in Sample A and FLOS(2005).

Both samples A and B cover the years 1992 to 2005, a period in which there was a lot of concern about earnings quality, while the FLOS sample covers a longer period (from 1970 to 2001) for much of which there was not a lot of concern about earnings quality. The innate characteristics of sample firms used in deriving the earnings quality variables are in my samples are compared to those in FLOS(2005) in Panel 3 of Table 1.
The characteristics are comparable, but show that my sample firms are a little larger, have suffered more losses in the prior 10 year period.

The mean analyst following is 10.57 (median 8), the mean earnings surprise (absolute value) is 12%, sample firms earn a mean 3.83% return on mean assets which have a log of 6.63, and have suffered a mean of 1.8 losses in the prior 10 years.

Sample firms are relatively large, however this should only bias against my finding results due to the lower amount of variability than can be expected in the earnings quality variables.

4.5 UNIVARIATE CORRELATION ANALYSIS

Table 2 presents the Pearson correlation coefficients among the variables in the study. It reveals that all three proxies of forecast Boldness are significantly negatively correlated with the overall EQ variable Std_AQI and with InnAQ. Correlations between Boldness and the quality of the discretionary component variables, both the signed and absolute values are weak and insignificant. This implies that increased bold forecasting when the quality of earning is higher which is inconsistent with hypothesis 1.

As expected the earnings quality measures are themselves fairly strongly (and significantly) correlated. Std_AQI and InnAQ have an average correlation coefficient of 0.45 (p-value<.0001); while Std_AQI and absDAQ have an average correlation coefficient of 0.69 (p-value<.0001); and absDAQ and InnAQ a coefficient of 0.28 (p-value<.0001).

Table 2 shows that both proxies of forecast boldness, have the predicted positive correlations with analysts’ prior accuracy, analysts’ firm specific experience, forecast
frequency and firm size, consistent with prior literature. Univariate correlations show that *Boldness* is negatively correlated with *brokersize*, forecast *horizon* and *days elaps*.

My multivariate tests provide additional evidence on the associations between the dependent variables and the independent variables of interest (earnings quality). These tests include controls for factors which are likely to affect the hypothesized associations (which are likely to confound my univariate results). Finding from the multivariate tests are documented in the next section, Section 5 – Results.
5.0 RESULTS

Multiple Regression Results:

I report the results of tests of my hypotheses using multiple regression techniques in Tables 3 – 9. Hypotheses are tested using two proxies for forecast boldness – Condis and DHI.

Condis measures forecast boldness from the individual analyst’s forecast level. Tests using this measure therefore show the association between analysts’ forecast type (i.e. bold or herding) and firms’ earnings quality characteristics. The Condis proxy uses the absolute distance between the analyst’s revised forecast and the consensus forecast immediately before the issue of the forecast as a relative measure of forecast boldness.

The degree of herding index (DHI) is another proxy of forecast boldness used in the study. Based on the assumption that the forecasts for a firm’s earnings should roughly follow a normal distribution, and that herding will result in a more ‘tight’ distribution, DHI uses the percentage of forecasts that actually fall in the tails of the distributions to estimate herding behavior. DHI is therefore a measure of forecast boldness, or alternatively, an inverse measure of herding. Tests using DHI therefore reflect the association of analysts’ (all analysts forecasting the firm’s earnings) herding behavior/ forecast boldness with the firm’s EQ and EQ components.

All tests of hypotheses are based on OLS regressions that include industry and year fixed effects as a control for cross-sectional correlation in the panel data. (The coefficients on these dummy variables are not reported). Standard errors are robust to clustering for both firm and year effects. Test results are detailed in Tables 1-9.
5.1 RESULTS OF TESTS OF HYPOTHESES

5.1.1 \textbf{H(1): The association of the Quality of the Innate Accrual component with Analysts’ Forecast Boldness:}

5.1.1.1 \textbf{Tests at the forecast level -using Condis proxy of forecast boldness}

Results of tests of the association of forecast boldness with the quality of the innate accrual component show that innate accrual quality has an inverse association with bold forecasts. Table 3’s regression results using Condis as the dependent variable documents a positive coefficient on InnAQ which signifies a negative relationship between forecast boldness and innate accrual quality (as InnAQ is an inverse measure of the innate component of accrual quality). InnAQ has a positive coefficient of 1.66 in Model 1 and 1.58 in Model 2, both with \textit{p-values} of <.0001. (Models 1 and 2 are both tests of hypothesis 1 that use the same regression model but employ different proxies for the discretionary component variable). The positive coefficient on InnAQ implies that as it increases in value (that is, as firm variability and complexity increase- lowering innate quality) the value of Condis also increases (reflecting bolder forecasts).

This supports hypothesis 1’s prediction of a negative association. Results are therefore consistent with analysts responding to users’ greater demand for analysts’ advice (due to difficulty in understanding earnings with poor innate discretionary components), by competing to produce more accurate forecasts to gain greater visibility, enhanced reputations and higher compensation.

\textbf{Control variables}

The relationships between the dependent variable and control variables are consistent with the relationships documented in prior studies. I find forecast boldness
(Condis) increases with the analyst’s prior accuracy, forecast frequency, firm specific experience and brokerage size, but decreases with the number of firms the analyst follows and the days elapsed since the analyst’s prior forecast. However, I find an inverse relationship between forecast boldness and forecast horizon which is not consistent with the direct association found in the Clement and Tse (2005) study.

There are some differences between their sample and the one used in this study that may have contributed to the difference in results. While Clement and Tse (2005) also use forecasts of annual earnings, their sample forecasts are issued in an eleven-month period with the majority being released close to the end of the forecast period. The mean and median forecast horizon in their sample is 98 and 71 days respectively. Forecasts in my sample are taken in a much narrower window (approximately 3 months) and are made early in the year; the mean and median forecast horizon is 284 and 282 days respectively.

My results therefore may reflect a difference in analysts’ early forecasting behavior. That is, after the release of the annual report, the initial forecasts may be less bold than those released subsequently (within the next two months). This is consistent with more confident analysts (perhaps those with more firm specific experienced) quickly releasing a forecast when earnings are announced, and then other analysts herding on their private information. Thus the short sample period used in the study may not allow enough time for new information to be introduced to the market that would give analysts the confidence to make bolder forecasts as the horizon decreases. Barron et al. (2000) alludes to differences in analysts’ behavior when making forecasts early in the year.
They note such differences as less herding and more focus on core earnings rather than to reacting to management’s manipulations.

5.1.1.2 Tests at the firm level - using DHI as a proxy for forecast boldness

The significant inverse association between the innate component of accrual quality and the boldness of analysts’ forecasts is again documented in Table 4. Using DHI as a firm level measure of forecast boldness, an inverse association is indicated in both Models 1 and 2 by the positive coefficients on InnAQ (an inverse measure of the innate component of accrual quality). The regression coefficients 0.92 and 0.95 are both significant with \( p\)-values of <.0001.

This result supports hypothesis 1. It implies DHI is greater when InnAQ is higher- or that analysts’ bold forecasts increase as innate accrual quality falls. Consistent with the results using the ConDis proxy, it suggests that analysts make bolder forecasts for firms with complex business models and variable operating environments. I explain this by the likely greater investor interest in firms with poor innate accrual quality. The greater demand likely increases the incentive to be more accurate in order to be recognized as a skilled analyst and earn higher commissions.

Control variables

The relationships between the dependent variable and control variables are consistent with the relationships documented in the prior studies and with tests run using boldness measures at the forecast level.

I find forecast boldness increases with the analyst’s prior accuracy and firm specific experience, the size of the brokerage house, firm size and analyst following.
Boldness decreases as the mean number of firms analysts follow increases, and prior to the firms making equity issues.

Forecast boldness is significantly inversely related to the indicator variable for firms’ equity issuance (-0.01 p-value, <.0001). This suggests that analysts’ herding behavior increases for firms that are about to issue stock. A potential explanation for this is that the increased disclosure as well as the increase in the quality of disclosure usually associated with firms that intend to raise capital. Thus there may be greater consensus among analysts and hence higher reputational concerns for analysts who forecast far from the consensus—thus providing a higher incentive to herd.

Analyst following is shown to have a significant positive association with forecast boldness (0.01 p-value, <.0001). This is in line with analysts issuing bolder forecasts as the number of analysts following the firm increases. In order to differentiate themselves and be recognized for their skill and accuracy analysts may produce more private information and issue bolder forecasts to enhance their reputations as the competitive environment intensifies.

5.1.1.3 Comparison of results with prior studies

The finding of an inverse association between innate accrual quality and forecast boldness however is inconsistent with findings reported by at least two earlier studies. Olsen (1996) finds that herding increases with the unpredictability of earnings (based on Value Line’s earnings predictability index); and Kim and Pantzalis (2003) find that complexity (proxied by global and industrial diversification) exacerbates the analysts’ tendency to herd. Both studies use a ‘herding index’ to measure herding. Olsen (1996)’s
conclusions are drawn from a univariate analysis of the association of the unpredictability proxy and the herding index. While this approach is useful, it however does not control for other possible influences on herding. Univariate results reported in this study’s Tables 2(a) and 2(b) consistent with Olsen (1996) also reflect significantly negative correlations between the innate accrual component \((\text{InnAQ})\) and herding proxies \((\text{ConDis} \text{ and } DHI)^8\). This also implies that herding is higher the lower innate accrual quality (or the more difficult earnings are to predict. Univariate associations however often do not model a relationship precisely as the influence of other predictive variables are not simultaneously taken into account and results can lead to misleading inferences. This suggests that the multiple regression results should be more reliable.

In order to explain my results, I follow Olsen (1996) univariate approach and rank sample firms into 5 groups based on their innate accrual quality and calculate Olsen’s herding index for each rank of innate accrual quality. Table 9 shows that similar to Olsen (1996) I find (with the exception of the 5\(^{th}\) group) that the herding index increases as the innate accrual quality declines (as firm complexity increases). Results are similar when I use \(\text{Std}_A\text{QI}\) the overall EQ measure. Based on a univariate analysis therefore this study’s results would support Olsen (1996)’s conclusion that herding increases with complexity. However as the multiple regression approach controls for the influence of other variables on the dependent variable (herding) the results from that analysis provide a more reliable test of the association. After controlling for the variables found in prior studies to have an influence on herding, the results suggest a negative relationship between complexity and herding.

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8 Both \(\text{ConDis}\) and \(DHI\) are inverse measures of herding
Kim and Pantzalis (2003)’s study proxies ‘complexity’ in analysts’ forecasting as analysts’ forecasting the earnings of diversified firms, both geographically and industrially. They find that analysts’ forecasts for diversified firms, on average, display more herding than forecasts for domestic/focused firms. Kim and Pantzalis reason that forecasting earnings of diversified firms should be more difficult for analysts to forecast as these firms have more complex organizational structures and less transparent operations. However, the major objective of corporate diversification is to reduce risk of volatility in the firm’s earning and fortunes. As such diversified firms are likely to have more consistent (earnings) performance under a variety of economic conditions- which should make it easier rather than more complex, for analysts to forecast earnings.

My innate accrual quality proxy $\text{InnAQ}$ is constructed so that greater variability (e.g. in revenues and cash flow from operations) and complexity results in lower innate accrual quality. The inverse association between innate accrual quality and forecast boldness implies that herding is higher for firms with less variability. Kim and Pantazalis (2003) conclude that herding is higher for diversified firms- which by definition are firms with less variability. Thus the difference between the studies may rest only in the definition and proxies of complexity, as on closer examination, the empirical findings appear similar.

5.1.2.1 Summary of results at the forecast and firm levels

The consistency of results at both the forecast and firm levels reflects the strength and significance of the innate component as a major driver of analysts’ forecast boldness. Both test results are highly significant with $p$-values of $<.0001$. This result of bolder
forecasts emanating from more complexity and variability in innate factors is consistent with findings in Essay 1, which shows that forecast dispersion increases inversely with innate accrual quality (that is there is a wider range of forecasts for firms with greater complexity as reflected by higher values of InnAQ).

These findings are consistent with analysts responding to a higher demand for their services (Bhattacharya, et al., 2007 find investors have more difficulty valuing firms with poor EQ) by producing more private information (e.g. building detailed proprietary models) for more complex firms (i.e. lower innate quality). The factors relating to innate characteristics (e.g., variability in revenues and cash flows) relative to discretionary information (e.g., accounting policy changes and poor estimation) can be more objectively and precisely measured.

Further the lower the quality of the innate component, the weaker the earnings signal it emits and therefore the consensus forecast is likely to be relatively inaccurate forecasts more dispersed (as seen in Essay 1). These factors therefore lower the analyst’s risk of being penalized for an inaccurate bold forecast. As peer analysts’ forecasts will also be relatively inaccurate thus the market will likely assume that earnings are difficult to forecast and will not think the analyst is ‘dumb’ for being far away from the consensus.

5.1.2. **H(2): The association of the Discretionary Earnings Component with Analysts’ Bold Forecasting**

Tables 3 and 4 report the results of tests of hypothesis 2 (H2) using two measures of the quality of the discretionary component. The signed value of the signed value of
the discretionary component ($DAQ$) reflects the amount of variability in the earnings signal that is related to managements’ discretion. When $DAQ$ is negative this indicates that management used their discretion to reduce the variability in the earnings signal, thus making it easier for analysts to accurately forecast future earnings. I therefore expect that bold forecasts will be negatively associated with this signed measure of the quality of the discretionary component, as lower values of $DAQ$ signify easier forecastability.

The main measure of the quality of the discretionary component is the absolute value of the discretionary component, $absDAQ$. It is the absolute size of the difference between the actual and the predicted variability (based on the firm’s innate factors) in the earnings signal. Analysts have an expectation of the predicted variability of the firm’s earnings. When actual volatility of the earnings signal deviates from their expectation, analysts should face the same level of difficulty explaining deviations that increase volatility (positive $DAQ$) or alternatively explaining deviations that reduce volatility (negative $DAQ$). The absolute value of the component $absDAQ$ provides a better test of analysts’ true understanding of managerial discretion because this proxy measures the magnitude of deviations rather than their signed values.

5.1.2.1 H2(1)- Tests at the forecast level -using Condis as proxy for forecast boldness

Table 3 reports the regression results of the discretionary components association with forecast boldness at the analysts’ forecast level. Model 2 uses the signed $DAQ$ variable as the dependent variable, while Model 1 uses the absolute value of the discretionary component $absDAQ$.  


Model 2, consistent with expectations, shows that $DAQ$ is negatively associated with $ConDis$ (coefficient $-0.58$, $p$-value $0.0117$). This is consistent with expectations and implies that when managers use their discretion to make the earnings signal more clear (e.g. by reducing the variability) analysts respond by issuing bolder forecasts. Conversely when management discretion increases the variability of the signal, analysts respond by issuing forecasts closer to the consensus.

Table 3, Model 1 also reports results using the absolute value of the discretionary accrual component, $absDAQ$, as the proxy for the quality of the discretionary accrual component. $ConDis$ is not associated with the quality of the discretionary component, $absDAQ$ (coefficient $0.18$, $p$-value $0.5212$). This result supports hypothesis 2(1) and suggests that, on average, analysts interpret increases and decreases in the variability of the earnings signal differently.

This lack of significance implies that the amount of discretionary information managers communicate through earnings does not affect the boldness of analysts’ forecasts. This result however is likely to be due to diversity in sample firms’ discretionary accrual quality; while some firms have informative discretionary components, others have noisy components. Firms whose managers provide value relevant discretionary information in earnings will have discretionary components that emit a strong signal of future earnings. However firms with noisy discretionary accrual quality components will emit weak signals of future earnings. Thus while, on average, there is no association between the absolute value of the discretionary component and forecast boldness, there is likely to be a positive relationship for the subsection of firms
with informative discretionary information which is offset by a lack of association for firms with noisy discretionary components.

To investigate this further, I divide the sample into two groups, firms with positive \( DAQ \) and firms with negative \( DAQ \). The managers of firms with negative \( DAQ \) values have used their discretion to reduce the variability of the earnings signal and thus made it easier for analysts (and other users) to forecast earnings. This is consistent with managers wanting to improve earnings’ predictive ability. As this objective is in line with providing value relevant information, I use sample firms with negative \( DAQ \) to proxy for firms with informative discretionary components and test whether there is a positive relationship between \( absDAQ \) and \( ConDis \). As Table 5 documents, I find that this subsample (proxying for firms with ‘informative’ discretionary) has a significant positive association with forecast boldness (coefficient 1.97, \( p\)-value 0.0259), while the subsample of firms with ‘noisy’ discretionary components do not (coefficient 0.36, \( p\)-value 0.1470).

This is supportive of diversity in the quality of firms’ discretionary accrual components. While some managers supply value relevant information in accruals (Subramanyam, 1996) other firms have noisy discretionary components which may be due to manipulative accounting or corrections of poor estimates and errors in accruals.

5.1.2.2 H2(1) Tests using \( DHI \) as the proxy for forecast boldness

Table 4 reports the results of the association of the quality of firms’ discretionary component with analysts’ forecast boldness. Model 1 uses the signed value of the discretionary component, \( absDAQ \) while Model 2 uses the absolute value, \( DAQ \). Neither
of the proxies for the quality of the discretionary component is significantly related to the herding index, *DHI* as both coefficients (coefficients 0.09 and –0.05 respectively) are insignificant (*p*-values 0.3177 and 0.3035 respectively).

This implies that from the firms’ perspective the boldness of analysts’ forecasts, and analysts’ herding behavior, are not associated with the discretionary component of accrual quality. This is in line with expectations as explained below.

The *DHI* proxy increases when the number of forecasts in the tails of the distribution is larger than expected based on a normal distribution. These ‘extreme’ forecasts which are furthest from the mean forecast are more likely to have larger innate values (accruals related to the firm’s variable and complex operations) than discretionary values since the innate component is on average much larger than the discretionary component and therefore by virtue of its size is more likely to ‘qualify’ the forecast as an ‘extreme’ one.

Table 1 shows that the mean and median values of the innate component are twice the size of the mean and median values of the discretionary component. Hence, as the innate component (of accrual quality related to the firm’s operational complexity and variability) plays a larger role in the determination of earnings quality than its discretionary counterpart, it should also be a more significant contributor to the variability in analysts’ forecasts (as seen in Essay 1) and hence should be more likely to account for more extreme forecasts, than the smaller discretionary component. This is portrayed by the results of testing H2 at the firm perspective, as documented in Table 4.

From the firm’s perspective therefore, bold forecasts – a larger than expected number of forecasts in the tails of the distribution, is not likely to be related to the firm’s
discretionary component of accrual quality. This relatively small component of earnings is not likely to account for large variations from the consensus earnings forecast and therefore from a firm perspective are not associated with bold forecasts.

5.1.2.3 H2(1): Summary of results at the forecast and firm levels

At the forecast level regression results show that the signed value of the $DAQ$ variable is significantly negatively associated with forecast boldness. This suggests that when managers provide discretionary information in order to make it easier to forecast earnings (i.e. managers use their discretion in earnings to reduce the variability of the earnings signal) analysts respond with bolder forecasts.

The absolute value of the discretionary component affords a more stringent test of analysts’ understanding of managers’ discretionary information than its signed counterpart. Unlike $DAQ$ (the signed component) which reflects managers’ either reducing variability (negative $DAQ$) in the earnings signal or increasing the variability (positive $DAQ$), the absolute value looks at analysts’ ability to incorporate deviations based on their magnitude (that is irrespective of whether deviations are positive or negative) from expected variability in the earnings signal.

When however the absolute size of the discretionary component ($absDAQ$) is used to proxy for the discretionary component of accrual quality, regression coefficients indicate that there is no significant relationship between the absolute value of the discretionary component and analysts’ bold forecasting / herding behavior at either the forecast or the firm level.
At the forecast level, the lack of significance appears to be the result of two factors. First the diversity in quality of firms’ discretionary components (which leads to a weakening of the positive association of firms’ informative discretionary components with the insignificant association of firms’ with noisy components); and second the average analyst’s low level of understanding of firms’ discretionary components (which results in a lower level of incorporation of discretionary information in analysts forecasts, thus again reducing the power of the association of forecast boldness with the discretionary component).

Hypothesis 2 further explores the second factor, differences in analysts’ understanding of managements’ discretionary information. Further investigation of the first factor, how diversity in the quality of firms’ discretionary components affect the overall association with forecast boldness is discussed below.

Investigating the impact of diversity in the quality of firms’ discretionary component

Using firms with negative values of their discretionary components to proxy for firms whose managers use their discretion to provide value relevant information, I test this sub sample’s association with forecast boldness and compare it to the group with positive discretionary components.

The positive and highly significant coefficient on $absDAQ$ in the sub sample proxying for informative discretionary information suggests that increasing the amount of discretionary information will increase the boldness of analysts’ forecasts. However, for the sub sample of firms with positive discretionary components, regression results show that there is no significant association between the size of the discretionary component and forecast boldness. This is expected as firms with positive discretionary components
are likely to have noisy discretionary components, as managers have used discretionary information to increase the variability of the earnings signal.

5.1.3 H2(2): Tests of using Condis as the proxy for forecast boldness

Hypothesis 2(2) tests whether analysts with more firm specific experience have a stronger (than their peers with less firm specific experience) association between forecast boldness and the discretionary earnings component. This is a joint test of the informativeness of the discretionary accrual component and of whether greater firm experience improves analysts’ understanding of managements’ discretionary information.

The empirical literature finds that analysts do not fully understand the information in accruals (Bradshaw, Richardson and Sloan, 2001). However, while on average this has been shown to be the case, analysts with more firm experience should be more familiar with managements’ reporting incentives and prior accuracy and therefore are likely to understand managements’ discretionary information. H2(2) tests whether these analysts with more firm specific experience capitalize on their relative advantage over their peers by producing bolder forecasts. Clement and Tse, 2005 find that bolder forecasts are more accurate and accuracy is positively associated with reputation and remuneration (Stickel, 1992).

This hypothesis is tested at the forecast level using ConDis and results are reported in Table 6. An added variable $HXabDAQ$ (an interaction of high firm experience with the discretionary component) in the regression facilitates an examination of whether experienced analysts have a higher association of the absolute value of the discretionary component with forecast boldness than their peers with less firm specific experience. Table 6 reports a positive and significant coefficient on $HXabDAQ$. 
(coefficient 0.59, *p*-value 0.0478) signifying that analysts with more firm specific experience have a higher association between their bold forecasts and the absolute value of the discretionary component.

This result again provides additional indirect evidence of the usefulness of the discretionary information in earnings. The overall positive association for these more experienced analysts between with forecast boldness and the discretionary component implies that their incorporation of discretionary information enable them to make bolder forecasts. As bolder forecasts are more accurate (Clement and Tse, 2005) this suggests that experienced analysts are able to extract value relevant information from managements’ discretionary earnings information.

Also important is the implication that analysts over time gain a better understanding of firms’ discretionary accrual information. This helps to explain why more experienced analysts are more accurate. It also helps to reconcile the divergent views we have on analysts. On one hand the literature identifies them as expert financial statement users while many studies have found that they do not understand accruals.

5.1.4 **H(3): The association of the Earnings Quality with Analysts’ Bold Forecasting**

5.1.4.1 Results of Tests of H(3) at the forecast level –(using the ConDis proxy)

Table 7 reports the results of tests of the association between firms’ overall earnings quality and the boldness of analysts’ forecasts. Regression results, using Condis show that the coefficient on $Std\_AQI$, the aggregate earnings quality variable, is insignificant (coefficient -0.32, *p*-value 0.14). This implies that there is no significant association between earnings quality and the boldness of analysts’ forecasts.
This lack of a significant relationship between EQ and forecast boldness indicates that decisions on analysts’ forecast type (bold or herding) are not driven by the firm’s aggregate EQ measure. The EQ measure is a composite of two sources of accrual information and quality-the innate and discretionary components. As seen in the results of testing hypotheses 1 and 2 (in Table 3) forecast boldness is negatively related to the innate component of accrual quality (InnAQ), and positively related to the discretionary component (DAQ). The offset of these opposite relationships in the aggregate EQ measure can be expected to reduce the significance of the EQ coefficient.

As forecast boldness is has a higher association with the EQ sub-components this suggests that analysts focus more on the accrual quality relating to innate factors and to managements’ discretionary information, than on an overall EQ basis when producing their forecasts. The results therefore suggest that analysts disaggregate the information in earnings quality and incorporate the more detailed information into their forecasts. This is consistent with Barth et al. (2001) and Dechow et al. (1998) who find that disaggregating earnings information increases predictive power.

Control variables

The relationships between the dependent variable and control variables are consistent with the relationships documented in the tests of the previous hypotheses.

5.1.4.2 Results of Tests of H(3) at the firm level- (using DHI as the proxy)

Table 8’s regression results reflect a significantly positive association between Std_AQI and DHI. Std_AQI’s coefficient is positive and significant (0.10 p-value 0.0235) indicating that higher values of Std_AQI (poorer EQ) are associated with higher
values of \textit{DHI} (bolder forecasts). This implies that, as hypothesized, the likelihood of analysts’ issuing bold forecasts is higher when firms’ EQ is lower.

This is consistent with analysts competing to gain a competitive advantage when EQ is poor and the demand for analysts’ investment advice is likely to be high. By issuing bolder forecasts reflecting more of their private information analysts aim to improve their forecast accuracy relative to their peers thereby enhancing their reputations, chances of being recognized as a skilled analyst, and remuneration.

\textbf{Control variables}

All control variables are significant and in line with expectations. The relationships between the dependent variable and control variables are consistent with the relationships documented in the prior studies and with tests run using boldness measures at the forecast level.

5.1.4.3 \textbf{Summary of results at the forecast and firm levels}

Tests of analysts’ forecast boldness and EQ at the forecast and firm levels afford two different perspectives on forecast boldness and how EQ and its sub-components are associated with it.

Tests from the forecast perspective reflect how EQ (or its sub-components) are related to analysts’ willingness to move away from the most recent consensus forecast. Regression results at the forecast level (using the \textit{ConDis} proxy for boldness) imply that the boldness of analysts’ forecasts is not associated with firms’ EQ. Instead results (reported in Table 3) suggest that analysts’ bold forecasting is more highly associated with the EQ sub-components- the innate and discretionary components. This suggests
that analysts disaggregate the information in EQ. Since the innate and discretionary components have opposite relationships with boldness, but the association with overall EQ is insignificant, this implies that both components may have strong associations with forecast boldness which are offset in the overall EQ measure.

On the other hand, regression results for tests at the firm level using the DHI proxy for boldness or herding behavior reveal, as hypothesized, a significant inverse association between the firm’s EQ and analysts’ bold forecasting. This implies that analysts issue bolder forecasts for firms with lower EQ.

The difference in the results of the association of forecast boldness and EQ at the forecast and firm levels is likely caused to by differences in how the respective proxies capture analysts’ unobservable herding/boldness action. The forecast perspective affords a more direct measure of herding by measuring the distance analysts forecasts move away from the consensus. From the firm’s perspective DHI gives an indirect measure of herding as it makes inferences based on the distributional properties of the all the forecasts made within a specified period.

The DHI measure gives more weight to the innate (the larger) component of EQ. Due to its relatively larger size the innate component is more likely (than the discretionary component) to be associated with forecasts further away from the mean and in the extremities of the distribution. The firm perspective therefore shows how EQ (and its components) are associated with (analysts’ boldness) more extreme forecasting. The results indicate that overall, EQ (like its dominant innate component) is negatively associated with analysts’ bold forecasting.
6.0 CONCLUSION

This essay provides empirical evidence of the association between firms’ earnings quality and analysts’ forecast boldness and/or herding behavior. Using an accrual based earnings quality proxy adopted from FLOS (2005) which facilitates the segregation of earnings quality into its sub components - innate accrual quality (the quality of accruals related to the complexity of the firm’s operations) and discretionary accrual quality (the quality of accruals based on managements’ discretion), I investigate how earnings quality and its sub-components are related to forecast boldness and / or herding behavior. Forecast boldness is measured by the size of the deviation of analysts’ revised forecasts from the consensus forecast.

The study uses OLS regression analysis in tests of these associations. Fixed effect dummies for firm and year are included in all regression models to control for cross sectional correlation in the panel datasets. Additionally based on Gow et al. (2009)’s findings, two-way cluster-robust standard errors are employed to further correct for any remaining serial and cross-sectional dependence, so that the inferences obtained from the analysis of the panel datasets are valid. Several interesting insights into analysts’ bold forecasting and its relationship with EQ are gained.

Results suggest that analysts’ produce more bold forecasts when investors have greater difficulty understanding firm value. Results are strongest when firms have poor innate accrual quality. These firms’ variable and complex operating environments require larger amounts of management judgment and estimation to determine firm performance. The high level of estimation produces a noisy earnings signal of future firm performance. This high level of information asymmetry means that investors are
more uncertain about future firm value and are likely to demand more investment advice from analysts.

The study’s results are consistent with analysts competing with peers to provide this advice through bolder forecasting. By issuing bolder forecasts which reveal more of their private information, analysts not only gain greater visibility, but in addition are likely to improve their accuracy (Clement and Tse, 2005) and reputations which facilitates the attraction of increased business and higher remuneration.

Prior literature documents analysts’ averseness to being classified as having poor forecasting ability (Scharfstein and Stein, 1990). Analysts’ may produce bolder forecasts in environments where innate accrual quality is relatively poor as the relative evaluation penalties for diverging from the consensus in this environment should be lower (given the greater diversity in estimates and lower accuracy of forecasts emanating from the weak signal of the firm’s future performance).

The results contribute to both the analysts’ forecasting and earnings quality literatures. I find evidence that supports the (now oft debated) view that analysts are effective capital market intermediaries. Results show that analysts make bolder forecasts (reveal more of their private information) when investors need more information for investment decisions (e.g. when the earnings signal) and herd (reveal less private information) when investors require less information. By revealing more of their private information when future earnings are more difficult to forecast (in terms of innate characteristics), analysts’ are providing more/less information based on the market’s demand and thus are being effective in their capital market intermediary role.
The study also provides a rational motivation for analysts’ herding behavior. Low investor demand for analysts’ investment advice and private information reduces analysts’ incentives to compete with their peers to gain greater visibility in order to attract a larger client base and higher remuneration. Given the high probability that the consensus forecast is fairly accurate (as found in Essay 1) and that the market will evaluate the analyst’s ability relative to his peers, the consensus provides a safe ‘bet’ for estimating earnings. As the average analyst in the study follows 25 firms, time constraints and time pressure is likely to make herding an attractive option when investors’ demand for investment advice on the firm is low and where the consensus is likely to be correct.

The study’s findings are also consistent with analysts being expert financial statement users. As bold forecasting is associated with EQ sub-components rather than with overall EQ, this implies that analysts disaggregate the information in earnings and incorporate the more detailed information into their forecasts. This may be related to Barth et al. (2001) and Dechow et al. (1998)’s findings that disaggregating earnings information increases predictive power. Future research on disaggregating accrual quality information should investigate whether disaggregating EQ into its innate and discretionary sub components increases predictive power.

Tests on forecast boldness’ association with the absolute value of the discretionary component also produced significant findings. As hypothesized, results indicate that the size of the firm’s discretionary component is not associated with analysts’ forecast boldness. This lack of significance in this association is attributed to two factors. The first relates to diversity in firms’ discretionary accrual quality. Some
firms have discretionary components based on managements’ value relevant information while others have noisy discretionary components (Guay et al., 1996; FLOS, 2005). This reduces the average reliability of the discretionary component and analysts’ confidence in reflecting discretionary information in their forecasts.

The second factor relates to analysts’ skill in understanding managements’ discretionary signals. Prior literature finds that analysts do not understand the information in accruals (Xie, 2001). Analysts’ poor understanding of the discretionary information therefore will negatively impact the analyst’s confidence to issue bold forecasts. The association between the discretionary component and bold forecasts therefore is weakened by analysts’ poor understanding of managements’ discretionary information.

While the study’s results are consistent with prior literature’s documentation of analysts on average exhibiting a low level of skill in understanding and correctly incorporating managements’ discretionary information, I investigate whether analysts with greater firm specific experience (who are more familiar with firm performance and managers’ ability) have more confidence in incorporating managers’ discretionary information to produce bolder forecasts. The positive association between experienced analysts’ forecast boldness and the size of the discretionary component (which is significantly higher than that of their less experienced peers) has two important implications.

First, it suggests that analysts’ expertise in understanding management’s discretionary signaling improves with greater exposure to the firm; and second, given that bold forecasts are on average more accurate (Clement and Tse, 2005) greater reliance by
more experienced analysts on the discretionary component to produce bolder (more accurate) forecasts provide indirect evidence supporting that on average management provides value relevant information through their discretion in earnings.

This is consistent with results in Essay 1 which finds an inverse association between forecast error and the size (absolute value) of the discretionary component, implying that on average the discretionary earnings component is informative. Both Essays 1 and 2 highlight the importance of the innate component of accrual quality thus Essay 2 provides additional evidence that complements the evidence in Essay 1.

Essay 2 in addition, extends our understanding of EQ’s association with the boldness of analysts’ forecasts and / or analysts’ herding behavior. It shows that herding is higher when earnings quality is higher and this is likely related to low demand for analysts’ investment advice. The study also provides evidence supporting the view that analysts are effective capital market intermediaries and users of accounting information. Despite their herding behavior, they provide investors with valuable information subject to the limitations of the quality of the discretionary component. Finally the study shows that analysts with more firm specific experience issue bolder forecasts the larger the size of the firm’s discretionary earnings component. This suggests that managers on average provide value relevant information and that analysts gain a better appreciation for their discretion by more exposure to it over time.

Any inferences made from this study are subject to important caveats regarding the appropriateness of the proxies used in the study. The validity of any measure of earning quality is dependent on the soundness of the model estimating these unobservable characteristics. As such all conclusions and inferences made in the study are dependent
on both the accuracy of the accrual models used in assessing earnings quality, and the suitability of proxies for herding and forecast boldness.
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