Analysts' Earnings Forecasts in Australia and Their Implications in the Extractive Industry

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DECLARATION

I certify that the work in this thesis entitled "Analysts' Earnings Forecasts in Australia and Their Implications in the Extractive Industry" has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree to any other university or institution other than Macquarie University.

I also certify that the thesis is an original piece of research and it has been written by me. Any help and assistance that I have received in my research work and the preparation of the thesis itself have been appropriately acknowledged.

In addition, I certify that all information sources and literature used are indicated in the thesis.

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ABSTRACT

Analysts' earnings forecasts have long been recognized as proxies for market expectations of future earnings because they are more accurate and have a stronger association with excess returns on the date of the earnings announcement than time-series models of earnings (Brown and Rozeff, 1978; Bradshaw et al., 2012). A large literature establishes the important role of analysts' forecasts. For example, Kothari (2001) suggests that "almost all models of valuation either directly or indirectly use earnings forecasts" (p. 144). The predictability of share returns is also associated with the properties of analysts' forecasts (Frankel and Lee, 1998; Jorgensen et al., 2012).

Australian research has increasingly used analysts' forecasts as proxies for expected earnings (Brown et al., 1999; Jackson, 2005; Beekes and Brown, 2006). While extensive research on analysts' forecasts focuses largely on the U.S. market, few studies relate to analysts' forecasts using Australian data. Motivated by the distinctiveness of the Australian setting with continuous disclosure to the stock market, and the prominence of the resources sector in the Australian economy, this thesis examines the properties of analysts' forecasts in Australia. The aims and objectives of the thesis are addressed in three papers, that is, a comparison of the relative accuracy of alternative earnings forecast measures, and the impact of the intensity of exploration and evaluation (E&E) activities on analysts' private information acquisition, forecast accuracy and bias in the extractive industry setting.

Specifically, the first paper (in Chapter Two) compares the relative accuracy of the consensus forecast against the most recent forecast in the month before the earnings announcement. It investigates how the number of analysts following a company and the timeliness of an individual analyst's forecast impacts on the differential accuracy of the consensus and the most recent forecast in Australia. The results suggest that, whilst in the late 1980s there is some evidence that the most recent forecast is more accurate than the consensus, since the early 1990s the accuracy of the consensus

forecast has consistently outperformed the most recent forecast. The forecasting superiority of the consensus forecast can be attributed to the aggregation value of the consensus outweighing the small timing advantage of the most recent forecast over the short forecast horizon examined in this study.

The second paper (in Chapter Three) examines whether analysts in the extractive industries adjust their private information development activities in response to the complexity of information about E&E activities. The results suggest that both the proportion of private information in their forecasts and the accuracy of their forecasts increase with the intensity of E&E activities. Additional analyses reveal that this effect is more pronounced for firms with substantial E&E activities but limited production activities, and that analysts' private information development activities are mainly related to the capitalized E&E expenditure.

The third paper (in Chapter Four) investigates whether the nature and extent of the uncertainty associated with E&E expenditure is a potential determinant of biases in analysts' forecasts, and also investigates an inter-temporal pattern of analysts' forecasts for firms with substantial E&E activities. The study finds that pessimism in analysts' forecasts increases with the intensity of E&E activities, suggesting that the effect of analysts biasing their forecasts to gain information access from managers is more pronounced for firms with higher levels of E&E expenditure. Moreover, analysts are more likely to follow a pessimistic-to-pessimistic pattern in response to greater exploration intensity, consistent with analysts' strategic use of pessimistic biases to increase their forecast error consistency.

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1 CHAPTER ONE

OVERVIEW OF THE THESIS

1.1 Introduction

Analysts' earnings forecasts have long been recognized as proxies for market expectations of future earnings because they are more accurate and have a stronger association with excess returns on the date of the earnings announcement compared to time-series models of earnings (Brown and Rozeff, 1978; Bradshaw et al., 2012). A large literature establishes the important role of analysts' forecasts. For example, Kothari (2001) suggests that "almost all models of valuation either directly or indirectly use earnings forecasts" (p. 144). The predictability of share returns is also associated with the properties of analysts' forecasts (Frankel and Lee, 1998; Jorgensen et al., 2012).

This thesis focuses on analysts' earnings forecasts in Australia by examining three aspects of analysts' forecasts in the Australian setting. Specifically, this thesis first identifies a superior measure of the accuracy of analysts' forecasts in Australia. Next, using the extractive industry as a special setting, the thesis evaluates the role of analysts in reducing the high information asymmetry exhibited in this industry. Finally, the thesis investigates analysts' incentives to bias their forecasts in environments with substantial uncertainties surrounding exploration & evaluation (E&E) activities in the extractive industry.

Because of the consistent use of analysts' forecasts as proxies for expected earnings in Australian research (Brown et al., 1999; Jackson, 2005; Beekes and Brown, 2006), it is important to understand the extent to which the expected level of forecast accuracy is realised and the reasons for the greater accuracy in the superior forecast measure in a non-U.S. setting with a distinct stock market disclosure environment and different industry composition. The first paper (in Chapter Two) examines the relative accuracy of alternative earnings forecast measures, the consensus and the most recent forecast, as measures of the market's earnings expectations prior to the earnings announcement.

Investors in extractive companies in Australia receive phenomenal returns on successful mineral or oil and gas discoveries but are nevertheless likely to face pronounced information asymmetry and inherently uncertain payoffs to exploration investment (How, 2000; Ferguson and Crockett, 2003; Poskitt, 2005). The exploration and evaluation (E&E) phase of an exploration project is arguably the most risky (IASB, 2010). The second paper (in Chapter Three) and the third paper (in Chapter Four) use the extractive industry as a specific setting and comprehensively examine associations between the intensity of E&E activities and analysts' private information search activities, forecast accuracy and bias.

The remainder of this chapter is organized as follows. Section 1.2 sets out the motivations for and background to this thesis. Section 1.3 outlines the research questions and objectives of this study and provides a brief summary of the three papers incorporated in this thesis. The contributions made by this thesis are outlined in Section 1.4. The organization of the thesis is explained in Section 1.5.

1.2 Motivations and Background

While extensive research on analysts' forecasts focuses largely on the U.S. market, few studies relate to analysts' forecasts using Australian data. Motivated by the distinctiveness of the Australian setting with continuous disclosure to the stock market, and the prominence of the resources sector in the Australian economy, this thesis focuses on analysts' forecasts in Australia.

A consensus forecast diversifies away idiosyncratic individual errors to gain value from the aggregation. The most recent forecast made over a shorter forecast horizon than the consensus is more timely. The trade-offs between the benefits of forecast aggregation and the timeliness of forecasts together with the non-U.S. setting motivate this thesis to identify the superior forecast measure for Australia. It does this in Paper 1.

While prior literature on the extractive industry recognizes substantial information asymmetry associated with E&E activities (Ferguson and Crockett, 2003; Poskitt, 2005), Paper 2 evaluates the role of analysts in reducing the high information asymmetry exhibited in this industry. Paper 3 examines biases in analysts' forecasts in the extractive industry where biased forecasts are more likely to affect investors' decisions because of the nature and extent of the uncertainty associated with E&E expenditure.

Prior research on analysts' forecasts in an international context finds considerable variation in analysts' forecast properties across countries. Chang et al. (2000) examine analysts' forecasts from 47 countries in 1996 and show a large discrepancy in their forecast properties: from an average forecast error of 2.3% for the U.S. to a forecast error of 71.2% for Slovakia. Similarly, with a sample of 42 countries and covering the period from 1988 to 1997, Ang and Ciccone (2001) report that analysts' forecasts differ significantly across countries, with an average forecast error of 60% and a dispersion of 31%. Among these countries, analysts' forecasts are the most accurate and least dispersed in Singapore, whereas Brazil has the highest average forecast error and the greatest forecast dispersion.

Several studies suggest that the systematic differences in analysts' forecast properties between countries are due to the great diversity in their accounting practices, disclosure standards, and industrial composition (Basu et al., 1998; Higgins, 1998; Hope, 2003). Using a sample of seven countries including the U.S., Japan and various European countries, Higgins (1998) investigates relations between analysts' forecast performance and the level of disclosures across countries. He finds that analysts' forecasts are more accurate for firms in countries that mandate extensive disclosures such as the U.S. and the U.K. than for firms in countries with less stringent disclosure requirements. Furthermore, using a sample of 22 countries, Hope (2003) provides evidence of considerable variation in the enforcement of accounting and disclosure standards across jurisdictions internationally and finds that strong enforcement of accounting and disclosure standards is associated with higher forecast accuracy.

In addition, Coën et al. (2009) observe that industrial structures differ considerably from one country to another; e.g., financial services are predominant while the resources sector is totally absent in Hong Kong and Singapore. They argue that this explains cross-sectional differences in the properties of analysts' forecasts. Sizable empirical evidence indicates the importance of industry effects on analysts' forecast accuracy (Brown, 1997; Jaggi and Jain, 1998; Capstaff et al., 2001). For example, taking a sample from nine European countries, Capstaff et al. (2001) show that analysts are the most accurate in the health care and public utility sectors, and the least accurate in the consumer durables and transportation sectors. They attribute their results to the different levels of earnings volatility for these industries. In summary, these studies highlight that the accounting practices, legal frameworks, and industry composition have a systematic impact on the properties of analysts' forecasts.

There are many similarities in the economic conditions in which both Australia and the U.S. operate: relatively developed economies, liberal economic conditions, and strong regulatory and legal frameworks. However, between the two countries there are also clear differences in accounting practices, disclosure standards and industry composition, which may potentially differentiate analysts' forecast performance.

Australia adopts a continuous disclosure regime whilst disclosure regulation in the U.S. is based on the periodic reporting model with quarterly reporting requirements. The resources sector is also more prominent in the Australian economy.

Compared with securities disclosure rules adopted by other developed countries, Australia pioneered the shift towards a continuous disclosure environment in 1994. The continuous disclosure rules contained in Chapter Three of the ASX Listing Rules require companies to disclose to the Australian Securities Exchange (ASX) information that would materially affect their security prices immediately they become aware of it. The rule received statutory backing in 1994. In contrast, disclosure regulation in the U.S. is based on the periodic reporting model under the 1934 *Securities Exchange Act*, and does not require continuous disclosure of material information.[1]

In the category of Regulation of Securities Exchanges, the Global Competitiveness Index 2013–2014 ranks Australia's continuous disclosure regime well ahead of other developed countries such as the U.S., the U.K. and Canada (Schwab, 2013). Countries like New Zealand, the U.K. and Canada adopted policies to introduce continuous disclosure obligations in the early 2000s (Heggen, 2005). In the U.S., consistent with the requirements of the *Sarbanes-Oxley Act* 2002, the Securities and Exchange Commission (SEC) mandated new disclosure requirements in Form 8-K to meet investor demand for "real-time" access to relevant and reliable information, to take effect in August 2004. The increasing importance of continuous disclosure in different jurisdictions makes it useful to examine the properties of analysts' forecasts in the Australian context. Indeed, Hsu et al. (2012) investigated inter-temporal changes in analysts' forecast properties over the period of 1988-2001 following the introduction and major changes to Australia's continuous disclosure regulation and

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[1] There are a number of circumstances in which Securities Exchange Commission (SEC) rules require disclosure of material information outside periodic reporting requirements. *Regulation Fair Disclosure* (*Regulation FD*), put into effect by SEC in October 2000, prohibits a company from selectively disclosing material non-public information unless simultaneous or prompt disclosure of the same information is made to the public.

enforcement, and found an improvement in analysts' forecast accuracy and dispersion in response to the proposal and introduction of continuous disclosure regulations.

With respect to industry composition in Australia, the resources sector (comprising minerals and oil and gas) has been an important part of the Australian economy since gold was discovered in the colony of Victoria in the 1850s. The sector has made a significant contribution to Australian economic development and social infrastructure since then. The development of iron ore mining in the Pilbara region of the State of Western Australia; the discovery and development of oil and gas in Bass Strait (the State of Victoria) and later on the North West Shelf (the State of Western Australia and the Northern Territory), and the major expansion of coal mining and exporting from the States of Queensland and New South Wales since the mid-2000s have cemented the resources sector as the cornerstone of the economy, supplanting agriculture as the nation's principal commodities export earner, and creating significant wealth for industries servicing this sector (Penney et al., 2012).

A few key statistics demonstrate the importance of the resources sector to the Australian economy. It is the nation's largest single export sector. In 2012-13, mineral and energy exports accounted for an estimated 86% (A$ 175 billion) of Australian commodity exports, and 58% of total goods and services exports (BREE, 2013). During that period, the mineral resources industries accounted for 8.6% (A$122 billion) of Australia's gross domestic product (ABS, 2013) and 266,000 employees, more than 50% above the level of three years earlier (BREE, 2013).

There are strong incentives for analysts in Australia to develop expertise in the extractive industry. A significant majority of exploration projects is funded by equity. Junior exploration companies in particular rely on equity financing to fund exploration because most of them do not generate revenue from mining production (SNL Metals Economics Group, 2013). The heavy reliance on equity investors to fund the capital intensive development of exploration projects makes it important for investors to understand the future implications of E&E expenditure. Investors also rely on analysts' information because of their prominent role in analysing, interpreting, and disseminating information to capital market participants.

The Australian context provides a powerful setting to examine the properties of analysts' forecasts. ASX is one of the world's leading markets for mining and oil and gas financing, with over 400 new junior resource floats during 2009 to 2013 alone (ASX, 2013b). The resources sector is central to the ASX, representing 28% of total market capitalization and 49% of all ASX listed companies by number (ASX, 2013a). Some of the world's largest diversified resource companies, including BHP Billiton and Rio Tinto, as well as many junior and mid-tier exploration companies are listed on the ASX. Given differences in accounting practices, disclosure standards and industry composition between Australia and the U.S., there are reasons to expect that the properties of analysts' forecasts in Australia may differ from the more widely-researched U.S. environment.

1.3 Aim and Objectives

The aim and objectives of the thesis are addressed in three papers, that is, a comparison of the relative accuracy of alternative earnings forecast measures, and the impact of the intensity of E&E activities on analysts' private information acquisition, forecast accuracy and bias in the extractive industry setting. Specifically, Papers 1, 2 and 3, respectively have the following objectives:

1. to identify a superior measure of the accuracy of analysts' forecasts in Australia;

2. to evaluate the role of analysts in reducing the high information asymmetry exhibited in the extractive industries; and

3. to investigate analysts' incentives to bias their forecasts in the extent of E&E activities.

1.3.1 Paper 1: Australian Evidence on the Accuracy of Analysts' Expectations: The Value of Consensus and Timeliness Prior to the Earnings Announcement

Analysts make and revise their earnings forecasts throughout the year as they incorporate new information into them. Their earnings expectations can be measured in a number of ways. Two widely used approaches are: a consensus forecast that aggregates individual analyst forecasts and is often defined as the mean or median of outstanding individual analyst forecasts at any point in time, and a single, most recent forecast provided by an individual analyst. A consensus forecast diversifies away idiosyncratic individual error to gain value from the aggregation. The most recent forecast made over a shorter forecast horizon than the consensus is more timely.

Paper 1 compares the relative accuracy of the consensus forecast versus the most recent forecast in the month before the earnings announcement and investigates how the number of analysts following a company and the timeliness of an individual analyst's forecast impact on the differential accuracy of the consensus and the most recent forecast in Australia. The paper investigates the extent to which the expected level of forecast accuracy is realised and the reasons for the greater accuracy in the superior forecast measure using Australian analyst forecast data. Specifically, this study proposes the following hypotheses:

H1: *The consensus forecast is more accurate than the most recent individual analyst earnings forecast.*

H2: *The greater forecast accuracy of the consensus forecast is due to the number of analysts contributing to the consensus.*

Data on one year ahead analysts' forecasts of annual earnings per share (EPS) are obtained from the I/B/E/S International Summary and Detail History files. The sample includes companies traded on the ASX, and with at least one I/B/E/S consensus forecast available and two analysts following for the period from fiscal 1987 to fiscal 2007 from the I/B/E/S International Summary History file. Because the consensus forecast is compared with the most recent forecast for a particular company and year, the most recent company-year individual analyst forecasts prior to the earnings announcement are extracted and matched from the I/B/E/S International Detail History file. The final annual earnings forecast sample to test the hypotheses yields 4,358 firm-year observations, representing 862 unique firms. Significance tests of difference in accuracy are used to determine whether the consensus is more accurate than the most recent forecast. The ordinary least squares (OLS) cross-sectional regression is estimated for each year and the Fama-MacBeth (1973) procedure is followed to examine the factors associated with the greater forecast accuracy in the superior forecast measure.

Paper 1 addresses the first objective of the thesis, that is, to identify a superior measure of the accuracy of analysts' forecasts in Australia, being a non-U.S. market with a distinct disclosure regime and different industry composition. The findings of this study set the methodological approach for the other two papers by providing evidence that the consensus forecast is a better measure of the market's earnings expectations and that the greater accuracy of the consensus forecast comes from averaging out idiosyncratic error in individual analyst forecasts.

A manuscript based on this paper was published in 2010 in issue 1 of the *Accounting Research Journal*.

1.3.2 Paper 2: Exploration Intensity, Analysts' Private Information Development and Their Forecast Performance

Paper 2 examines the relations between the intensity of E&E activities and analysts' private information development activities and their forecast performance. Specifically, it examines whether the greater intensity of E&E activities motivates analysts to acquire and process relatively more private information to meet investor demand and whether this affects the accuracy of their forecasts. The paper further investigates factors that are associated with analysts' reliance on private information and their forecasting ability on E&E activities. The study formulates and tests the following hypotheses:

H1: *The proportion of private information contained in analysts' forecasts is positively associated with the intensity of E&E activities.*

H2: *The accuracy of analysts' average forecasts is positively associated with the intensity of E&E activities.*

Annual E&E expenditure data are manually collected from the financial statements of ASX-listed extractive companies through the Morningstar DatAnalysis database. Analyst forecast data are obtained from the I/B/E/S International Summary History File. Financial statement data are obtained from the Morningstar DataLink database. Share prices and market capitalization information are sourced from the CRIF Share Price and Price Relative (SPPR) database. Of more than 3,000 firm-years reporting E&E expenditure in annual reports or for which E&E expenditure can be estimated using other financial statement line items for the period between the fiscal years 1993 and 2009, 781 firm-years with analyst forecasts available in the I/B/E/S database are included in the final sample, representing 166 unique firms. The substantial reduction in sample size is consistent with the fact that many listed junior exploration companies with no product sales are unlikely to attract analyst following. The Barron et al. (1998) analyst consensus construct is used to capture the average proportion of private information conveyed in analysts' forecasts. The OLS pooled cross-sectional regressions are estimated to test the hypotheses.

Paper 2 addresses the second objective of the thesis by evaluating the role of analysts in reducing the high information asymmetry associated with E&E activities in the extractive industries. Investing in extractive companies presents investors with several challenges, including pronounced information asymmetry and complexity of non-financial information. The results show that market participants can benefit from analysts' expertise in developing private information and can use analysts' forecasts to expand their information set when investing in extractive companies with high exploration intensity.

A manuscript based on this paper was co-authored with the PhD supervisors. The contribution made by the PhD candidate, in terms of percentage, was 80% for this chapter.

1.3.3 Paper 3: Exploration Intensity and Analyst Forecast Bias

Paper 3 examines whether the nature and extent of the uncertainty associated with E&E expenditure is a potential determinant of biases in analysts' forecasts, and also investigates an inter-temporal pattern of analysts' forecasts for firms with substantial E&E activities. The paper further investigates whether the different levels of production and E&E activities a firm engage in have an impact on the relation between the exploration intensity and analysts' forecast biases. Two hypotheses are proposed:

H1: *The pessimistic bias in analysts' forecasts throughout a fiscal year is more pronounced for firms with greater exploration intensity.*

H2: *A pessimistic-to-pessimistic pattern in analysts' forecasts within a fiscal year is more pronounced for firms with greater exploration intensity.*

Analyst forecast bias is measured as the signed forecast error, that is, the difference between actual earnings and consensus forecasts, scaled by share price. The final sample includes 7,016 firm-year monthly forecast observations containing E&E expenditure in annual reports or for which E&E expenditure can be estimated using other financial statement line items for the period between the fiscal years 1993 and 2009, with consensus forecasts issued between the prior and current year's earnings announcements. The sample represents 794 firm-years and 167 unique firms. The OLS pooled cross-sectional regression is used to test for a relationship between the intensity of E&E activities and analyst forecast bias, and the logistic cross-sectional regression is used to test for the probability of analysts exhibiting a pessimistic-to-pessimistic pattern in their forecasts for firms with substantial E&E activities.

Paper 3 addresses the third objective of the thesis by investigating the effect of the nature of the firms' assets on analysts' incentives to bias their forecasts to improve management access and forecast accuracy. Analysts strive to develop private information to better incorporate and account for the high level of uncertainty surrounding E&E activities. Managers are in a position to help analysts form accurate expectations of future earnings realizations (Hutton et al., 2012), and they have incentives to report earnings that meet or exceed analysts' forecasts (Bartov et al., 2002; Kasznik and McNichols, 2002; Mikhail et al., 2004). In anticipating management's reporting incentives, analysts may incorporate a pessimistic bias into their forecasts to help managers beat those forecasts so as to curry favour and, leading to better access to managerial information. This chapter provides evidence on the increasing effect of analysts biasing their forecasts in the extent of E&E activities to gain information access from managers.

1.4 Contributions

This thesis makes several contributions to the academic literature on analysts' forecasts, intangible assets and extractive industries. Primarily, it provides evidence on the properties of analysts' forecasts in the Australian setting. It also evaluates the role of analysts in reducing the high information asymmetry associated with E&E activities, and investigates analysts' incentives to bias their forecasts in environments with substantial uncertainties surrounding E&E activities in the extractive industries.

Paper 1 contributes to prior research on Australian analysts' forecasts three ways. First, this study provides evidence on the accuracy of the consensus in reducing idiosyncratic error by diversifying across analyst forecasts in a market with a distinct disclosure regime and different industry composition. Given the consistent use of analysts' forecasts as proxies for expected earnings in Australian research, this study provides insights into the extent to which the expected level of forecast accuracy is realised and the reasons for the greater accuracy in the superior forecast measure. Second, this study provides direct evidence of the accuracy of alternative forecast measures, the consensus and the most recent forecast, as measures of the market's earnings expectations prior to earnings announcements. Recent studies document improvements in the timeliness of consensus forecasts, but these studies do not directly compare the accuracy of the consensus and the most recent forecast (Barron and Stuerke, 1998; Brown, 2001; Ramnath et al., 2005). Last, the study also supports the market practitioners' views, as evidenced by press reports, that the consensus forecast is a better measure of the market's earnings expectations.

Paper 2 makes contributions to the literature as follows. First, it adds to the literature studying information asymmetry in the extractive industries. Notwithstanding the major global importance of the extractive industries, there is a surprisingly small number of studies on the extractive industries in a capital markets context. This study provides evidence of positive associations between the intensity of E&E activities, analysts' private information development activities and their forecast performance. While prior research on the extractive industries recognizes the high information asymmetry associated with E&E activities (Ferguson and Crockett, 2003; Poskitt, 2005), the findings of this study suggest that analysts are able to reduce the high information asymmetry associated with E&E activities, by engaging in private information development and using it to improve their forecast accuracy.

Second, this study provides further empirical evidence on the impact of intangible assets on analysts' forecast performance. The relevant question is whether the complex nature of intangible assets adversely affects analysts' forecast accuracy. Gu and Wang (2005) find that different types of intangible assets are associated with differential accuracy of analysts' forecasts. Forecast accuracy is significantly lower for firms whose intangible assets are technology-based (R&D), and increases for intangible assets subject to intangibles-related regulations in the biotech, pharmaceutical, and medical equipment industries. The results from this study complement Gu and Wang (2005)'s findings, suggesting that apart from intangible-related regulations, the various degrees of "diversity" and "innovativeness" pertaining to the different types of intangible assets have an impact on their relation to analysts' forecast accuracy. Analysts are able to improve their forecast accuracy using their private information acquisition and processing skills for firms whose intangible assets have limited scope for diversity and innovation.

Paper 3 adds to the literature that investigates the effect of firm characteristics on analysts' strategic use of biases to gain information access from managers. Das et al. (1998) suggest that the firm characteristic of earnings predictability is a potential determinant of analyst forecast bias to ensure access to managerial information. Lim (2001) also predicts that analysts trade off bias to improve management access and forecast accuracy for firms with greater uncertainty about earnings or poor financial disclosures. In contrast to those studies, this study sheds some light on the effect of the nature of the firms' assets on analyst forecast bias. The degree of uncertainty is greater for investments in intangible assets than other types of capital investments (Kothari et al., 2002). Analysts expend more resources and effort in developing private information for firms with higher levels of intangible assets (Barth et al., 2001; Barron et al., 2002). The results of this study show that analysts' forecast bias increases with the extent of E&E activities, consistent with analysts trading off biases to improve management access and forecast accuracy for firms with substantial uncertainties about the realization of future economic benefits associated with intangible assets.

It also contributes to the literature that examines the effect of management's incentives on analysts' forecast bias. Because the payoffs to E&E expenditure are highly uncertain, this uncertainty engages analysts in a constant search for information to better understand and interpret geological and other relevant data on the future prospects of E&E activities. Managers have a central role in generating estimates of the future as they design and execute their firm's strategy, and they have incentives to report earnings that meet and exceed analysts' forecasts. Analysts' forecast biases depend on managers' incentives (Beyer, 2008). In other words, analysts are willing to accommodate managers' demands so as to curry favour (Ke and Yu, 2006; Libby et al., 2008). This study focuses on whether the nature and extent of the uncertainty associated with the firms' assets is related to analysts' strategic use of biases to please management so as to gain better information access.

Finally, with various patterns of bias in analysts' forecasts documented by prior research (Francis and Philbrick, 1993; Matsumoto, 2002; Richardson et al., 2004; Hilary and Hsu, 2013), this study investigates an inter-temporal pattern exhibited in analysts' forecasts for firms with high levels of E&E expenditure. The findings of this study suggest that analysts follow a pessimistic-to-pessimistic pattern in response to greater exploration intensity. The study extends the work by Hilary and Hsu (2013) by documenting analysts' strategic use of pessimistic biases to improve their forecast error consistency in environments with inherent uncertainty and high information asymmetry.

1.5 Organization of the thesis

The reminder of the thesis is organized as follows. Chapters Two to Four comprise the three self-contained papers. The relevant tables and references for each chapter are incorporated into the respective chapter. Chapter Five is the concluding chapter which summarizes the findings of each of the three papers and draws conclusions and implications. It also discusses the limitations of the thesis and suggestions for future research.

2 CHAPTER TWO

Australian Evidence on the Accuracy of Analysts' Expectations: The Value of Consensus and Timeliness Prior to the Earnings Announcement

2.1 Introduction

It is well established in the literature that analysts' earnings forecasts are used as proxies for market expectations of future earnings because they are more accurate and have a stronger association with excess returns on the date of the earnings announcement than time-series models of earnings (Brown and Rozeff, 1978; Fried and Givoly, 1982; Brown et al., 1987a, 1987b). Analysts' earnings expectations can however be measured in a number of ways. Two widely used approaches are a consensus forecast that aggregates individual analyst forecasts at any point in time and a single, most recent forecast provided by an individual analyst.[2]

A consensus forecast diversifies away idiosyncratic individual error to gain value from the aggregation. The most recent forecast made over a shorter forecast horizon than the consensus is more timely. Tradeoffs between the benefits of forecast aggregation and the timeliness of forecasts motivate this study to compare the relative accuracy of the consensus and the most recent forecast. This study

[2] There is an alternative approach to derive a consensus forecast which is to vary component-forecast weights as a function of the expected accuracy of each forecast such as forecast age, broker size and analyst experience (Kim et al., 2001; Brown and Mohd, 2003; Butler et al., 2007). Because this approach is not widely used in the investment community or academic research, this study focuses on the consensus forecast defined as the mean or median of outstanding individual analyst forecasts at any point in time.

specifically examines whether the number of analysts following a company or the timeliness of an individual analyst's forecast is more strongly associated with the superior forecast measure.

Prior research in the late 1980s and early 1990s using data from the U.S. market examines the relative accuracy of alternative earnings forecast measures provided by standard sources of analysts forecast data such as I/B/E/S and shows that the most recent forecast is relatively more accurate than the consensus forecast (O'Brien, 1988; Brown, 1991). Brown and Kim (1991) find that the most recent forecast is more closely related to share prices than the consensus forecast. Based on these results, many studies use the most recent forecast as a measure of the market's earnings expectations (e.g., Brown, 2001; Bartov et al., 2002; Brown and Caylor, 2005). However, recent studies document that the consensus has become a more timely measure in the past decade due to improvements in analyst forecast data (Barron and Stuerke, 1998; Brown, 2001; Ramnath et al., 2005). These studies suggest that attempts have been made to include only relatively recent forecasts in the consensus to improve the timeliness of consensus forecasts. Taken together, these findings suggest that prior conclusions of the superiority of the most recent forecast may no longer apply due to the changing nature of consensus forecasts in more recent years.

Research in the Australian market has increasingly used analysts' forecasts as proxies for expected earnings (e.g., Brown et al., 1999; Beekes and Brown, 2006; Habib and Hossain, 2008).[3] Australian press reports overwhelmingly cite analysts' earnings expectations using the consensus rather than the most recent forecast.[4]

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[3] For example, Brown et al. (1999) examine properties of analysts' forecasts in different corporate disclosure environments. Beeks and Brown (2006) use analyst forecast accuracy as one of the indicators for the informativeness of a firm's disclosure to investigate the association between a listed Australian firm's corporate governance quality and its disclosure and the market response. Habib and Hossain (2008) use analysts' forecasts to examine whether Australian managers manage earnings in an attempt to meet or beat analysts' forecasts.

[4] For example, a search using text terms of "consensus forecast(s) or consensus estimate(s)" finds 800 articles in Australian key newspapers from January 1, 2007 to December 31, 2008 while a search using text terms of "latest analyst forecast or latest analyst expectations" finds 2 articles in the Factiva database.

While extensive research on analysts' forecasts is available for the U.S. market, there is relatively limited research related to analysts' forecasts using Australian data (e.g., Jackson, 2005; Brown et al., 2007; Aitken et al., 2008).[5]

This study contributes to prior research on Australian analysts' forecasts in several ways. First, this paper provides direct evidence of the accuracy of alternative forecast measures, the consensus and the most recent forecast, as measures of the market's earnings expectations prior to earnings announcements. Recent studies document improvements in the timeliness of consensus forecasts, but these studies do not directly compare the accuracy of the consensus and the most recent forecast. Given the consistent use of analysts' forecasts as proxies for expected earnings in Australian research and press reports, it is important to understand the extent to which the expected level of forecast accuracy is realised and the reasons for the greater accuracy in the superior forecast measure. Second, this study provides further evidence on the accuracy of the consensus in reducing idiosyncratic error by diversifying across analyst forecasts in a market with relatively few analyst coverage and a different disclosure regime. Last, it also confirms market practitioners' views, as evidenced by press reports, that the consensus forecast is a better measure of the market's earnings expectations.

The results suggest that, whilst in the late 1980s the most recent forecast is more accurate than the consensus during the period immediately prior to the earnings announcement, since the early 1990s the consensus forecast outperforms the most recent forecast. That is, the most recent forecast is, on average, less accurate than the most recent consensus available in the month prior to the earnings announcement. The accuracy of the consensus forecast consistently outperforms the most recent

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[5] An example of prior research relating to analysts' forecasts in Australia is Jackson (2005). Jackson presents evidence that analysts build their reputations by providing accurate forecasts, and that high reputation analysts generate more trading volume. Recent studies examine share price responses to Australian analysts' research quality and their stock recommendations. For example, Brown et al. (2007) study the market response to initiating recommendations made by analysts in terms of returns and share price responses. Aitken et al. (2008) examine the relation between analysts' research quality and price discovery.

forecast in 15 out of 17 more recent years, and the differences are significant for nine out of those 15 years. The number of analysts following explains the greater accuracy of the consensus. The aggregating value of the consensus outweighs the small timing advantage of the most recent forecast over the short forecast horizon examined in this study.

The results from the late 1980s are consistent with those of earlier studies using U.S. data that find that the most recent forecast is more accurate than the consensus (O'Brien, 1988; Brown, 1991). However, the results in more recent years indicate the opposite, consistent with improvements in the timeliness of forecasts included in consensus forecasts identified in prior studies (Barron and Stuerke, 1998; Brown, 2001; Ramnath et al., 2005). The recent results suggest that the greater accuracy of the consensus forecast comes from diversifying away idiosyncratic error in individual forecasts, conditional on only relatively recent forecasts being included in the consensus.

The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 develops the hypotheses. Section 4 describes the sample selection and data. Section 5 discusses the variable definitions and research methods. Section 6 reports the results of tests. Section 7 presents the results of additional analysis. Section 8 concludes.

2.2 Prior Research

2.2.1 The Aggregation Value of Consensus Forecasts

Analysts make and revise their earnings forecasts throughout the year as they incorporate new information into their forecasts. O'Brien (1988, p.53) suggests that: 'Since a diverse set of forecasts is available at any time for a given firm's earnings, composites are used to distil the diverse set into a single expectation'. A consensus forecast is a forecast that aggregates all information available to analysts. It is often defined as the mean or median of outstanding individual analyst forecasts at any point in time.

An aggregate forecast is expected to average out potential inefficiencies in how individual analysts process information and therefore provide more accurate future earnings expectations. For example, the I/B/E/S consensus forecast in the U.S. is more accurate and offers a better proxy for the market's earnings expectations than a single forecaster (Value Line) immediately before a quarterly earnings announcement (Ramnath et al., 2005). Their study shows that most of the consensus forecasting superiority can be attributed to the aggregation value. Because the consensus forecast aggregates expectations from various analysts and stockbroking firms who are covering a company, idiosyncratic analyst error is diminished through the aggregation process. Thus, the accuracy of the consensus is improved.

As suggested by Barron et al. (2008), the larger the number of analysts following and contributing to the consensus, the more the idiosyncratic analyst error is averaged out in determining the consensus forecast, and the higher is the accuracy of the consensus forecast. This suggestion motivates an examination of the association between the number of analysts following and the accuracy of consensus forecasts in this study.

The timeliness of individual forecasts included in the consensus forecast is important when evaluating its accuracy. Because not all analysts update their forecasts in a timely manner, the consensus forecast at any point in time includes both recent and potentially stale forecasts (Kothari, 2001). The inclusion of stale forecasts is likely to reduce the accuracy of consensus forecasts.

Many studies document that the consensus has become a more timely measure over time due to recent improvements in the timeliness and quality of analyst forecast data included (Barron and Stuerke, 1998; Brown, 2001; Ramnath et al., 2005).[6] These studies suggest that attempts have been made to include only relatively recent forecasts in the consensus. O'Brien (1988) finds that the consensus is significantly better than the most recent forecast when the consensus is relatively timely. That is, conditional on only reasonably timely forecasts being included in the consensus, an aggregate or consensus forecast is expected to diversify away idiosyncratic individual error and therefore provide more accurate future earnings expectations.

2.2.2 Timeliness of Analysts' Forecasts

O'Brien (1988) uses I/B/E/S individual analyst forecast data to compute and compare three alternative forecast measures: the mean, the median, and the most recent individual analyst forecast. She finds that the most recent forecast is more accurate than both the mean and median forecasts in the 1975 – 1981 period. More recent studies confirm that the accuracy of earnings forecasts improves as the earnings announcement date approaches (Lim, 2001; Ivkovic and Jegadeesh, 2004). These studies indicate that analysts are able to incorporate new information into their forecasts. This highlights the importance of the timeliness of forecasts for improving forecast accuracy.

In particular, the forecasts made over the short forecast horizon (i.e., in the period immediately prior to the earnings announcements) will be the most informative and accurate. As suggested by Ivkovic and Jegadeesh (2004), the analysts who update their forecasts most recently have access to all prior forecasts made by other analysts and will use them rationally in making their own forecasts. In addition, they may have early access to earnings information such as management's guidance on future earnings. Although company management can choose to provide earnings guidance at any point in time, any guidance they provide will be more accurate the closer it is

[6] Barron and Stuerke (1998) note improvements in the integrity of the I/B/E/S database. Brown (2001) documents improvement over time in the accuracy of I/B/E/S forecasts. Ramnath et al. (2005) find increased reliability of I/B/E/S forecasts. The increasing competition between forecast data providers may lead to these improvements. For example, First Call Corporation began to provide analyst forecast data in the early 1900s (Brown, 2001; Ramnath et al., 2005).

to the earnings announcement. If some analysts obtain early access to such information, then their earnings forecasts will be superior to others.[7] In this study, the most recent forecast is used to examine its accuracy in comparison with the consensus forecast.

2.2.3 Tradeoffs between Forecast Aggregation and Timeliness of Forecasts

The consensus forecast is characterised by the aggregation value from diversifying across idiosyncratic individual error. The most recent forecast made over a shorter forecast horizon is more timely. Brown (1991) investigates tradeoffs between the benefits of forecast aggregation and timeliness of forecasts. He adopts an approach of dropping stale forecasts from the consensus by using three timely forecast measures (i.e. the most recent forecast, an average of the three most recently issued forecasts and an average of all forecasts issued within the past 30 days). He finds that the comparative advantage of each forecast measure depends on company size. For large companies, the 30-day average is significantly more accurate than the most recent forecast; for small companies, the most recent forecast is more accurate than the other two forecast measures. Brown's results suggest that the forecast aggregation outweighs the timeliness of forecasts for large companies with more analysts following. In contrast, the most recent forecast shows its timing advantage for small companies for which the benefit of aggregation of individual analyst forecasts is ineffective. However, Brown does not directly examine the association between the number of analysts following and the accuracy of these forecast measures.

Tradeoffs between the benefits of forecast aggregation and timeliness of forecasts motivate this study to compare the accuracy of the aggregate consensus forecast and

[7] This argument appears to assume, however, that the few analysts updating their forecasts have information not available to the majority of analysts who choose not to update their forecasts, all else being equal. It is unlikely that selective briefings are widespread given the disclosure environment briefly discussed in the following section. Any ability of individual analysts to outperform the consensus close to the earnings announcement does, however, raise interesting questions regarding the source of any superior performance, and hence the need to examine previous results using U.S. data within other regulatory environments.

the most recent forecast. Specifically, this study examines whether the number of analysts following is more strongly associated with the superior forecast measure.

2.3 Hypothesis Development

Because analysts do not issue forecasts at prescribed times, there is variation in the age of forecasts included in the consensus. Forecast accuracy generally improves as the earnings announcement date approaches because analysts incorporate new information into their forecasts (O'Brien, 1988; O'Brien, 1990). If forecast age is the single most important factor associated with forecast accuracy (Clement, 1999; Jacob et al., 1999), then the more recent forecast is expected to be more accurate than older ones. Brown (1991) argues that the consensus forecast is less accurate than more timely forecast measures, including the most recent forecast, because the consensus includes stale forecasts. Stale forecasts reduce forecast accuracy because recent earnings information is omitted.

On the other hand, the consensus forecast is expected to average out the individual analyst's idiosyncratic error through the aggregation process, thereby improving forecast accuracy (Brown, 1993; Ramnath et al., 2005; Barron et al., 2008). If diversifying across individual idiosyncrasies is more important than discarding stale forecasts, then the consensus forecast that aggregates multiple analysts' forecasts may be more accurate than a single recent forecast.

Relative timeliness of the consensus forecast is also important when evaluating its accuracy. O'Brien (1988) shows that the consensus forecast is more accurate than the most recent forecast only when relatively recent forecasts are included in the consensus. Recent improvements in analyst forecast data including the I/B/E/S database are reflected in the consensus being a more timely forecast measure (Barron and Stuerke, 1998; Brown, 2001; Ramnath et al., 2005). Aggregating to reduce idiosyncratic error in the consensus is more effective when more timely individual forecasts are included in it.

This study investigates how the number of analysts following a company and the timeliness of an individual analyst's forecast impacts on the differential accuracy of the consensus and the most recent forecast in Australia. Like many smaller economies, the Australian market has relatively few brokerage firms and few analysts covering companies.[8] The limited number of brokerage firms and analysts tends to cover companies with high market capitalization, leaving small companies with a thin coverage at best. Since the market relies on the limited number of analysts providing coverage, it is important to purge idiosyncratic error from analysts' individual forecasts.

The disclosure environment, enhanced by continuous disclosure regulation since 1994, prohibits companies from briefing individual analysts with price sensitive information, which mitigates the ability of individual analysts to gain incremental information. For the short forecast horizon examined in this study, that is, during the period immediately prior to the earnings announcement, the aggregation value of the consensus forecast is expected to outweigh the timing advantage of the most recent forecast in the Australian context. Therefore the consensus forecast is expected to be more accurate than the most recent forecast, and the first hypothesis is:

H1: *The consensus forecast is more accurate than the most recent individual analyst earnings forecast.*

A possible explanation for the greater accuracy of the consensus forecast is the aggregation value resulting from including expectations of multiple analysts. If the relatively greater accuracy of the consensus forecast is largely explained by its aggregation value, then the difference in forecast accuracy should be related to the number of analysts contributing to the consensus. Specifically, the larger the number

[8] Using I/B/E/S data for U.S. companies, Ke and Yu (2006) report that 21.07 of analysts on average cover a company during 1983 – 2000. Barron and Stuerke (1998) show that the average number of analysts following from 1990 to 1994 is about 16 in their sample. In this study the average number of analysts per company is seven.

of analysts following and contributing to the consensus, the greater should be the accuracy of the consensus forecast. Based on this, the second hypothesis is formed as:

H2: *The greater forecast accuracy of the consensus forecast is due to the number of analysts contributing to the consensus.*

2.4 Sample and Descriptive Statistics

2.4.1 Sources of Data

Data on one year ahead analysts' forecasts of annual earnings per share (EPS) are obtained from the I/B/E/S International Summary and Detail History files. The Summary files contain the summary statistics on analyst forecasts, such as means, medians and standard deviations. The Detail files provide individual analyst forecasts and the date of each forecast issued. The summary data are calculated and reported by I/B/E/S on the basis of all outstanding forecasts as of the third Thursday of each month using the individual forecasts in the Detail files.[9]

The mean and median consensus forecasts are calculated using individual analyst forecasts to match the I/B/E/S summary consensus. The number of individual forecasts available to calculate forecast statistics, as at the publication date of the last I/B/E/S summary report prior to the earnings announcement, is matched against the number of individual forecasts included in the I/B/E/S consensus.[10] This approach enables the identification of individual forecasts included in the consensus and their forecast ages when considering the timeliness of the consensus. This consensus

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[9] While the policy is stated in terms of all forecasts, I/B/E/S does drop off stale forecasts when calculating its monthly summary statistics. I/B/E/S reports the number of analysts' forecasts included in the consensus and this number of forecasts is used to identify the forecasts assumed to be included in the consensus in this study.

[10] For example, if I/B/E/S reports 12 individual forecasts are included in the calculation of its summary consensus, then the most recent forecasts issued by 12 individual analysts as of the publication date of the I/B/E/S summary report will be used in the computation of forecast statistics.

forecast measure is checked against the I/B/E/S summary measure and the two measures are found to be closely matched.[11] Since the empirical results using the reconstructed consensus measure or the I/B/E/S summary measure are very similar, only the results obtained using the reconstructed consensus measure are reported in this study.

The corresponding actual earnings are obtained from I/B/E/S for comparability with the forecast. Earnings announcement dates are sourced from the Securities Industry Research Centre of Asia-Pacific (SIRCA) database.[12] The constituent list for the ASX 100 Index is obtained from the SIRCA database. Share prices and market capitalization information are obtained from the CRIF Share Price and Price Relative database (SPPR). Accounting information was sourced from the ASPECT database.

2.4.2 Sample Selection

The initial sample includes companies traded on the Australian Securities Exchange (ASX), and with at least one I/B/E/S consensus forecast available and two analysts following for the period from fiscal 1987 to fiscal 2007.[13] Consistent with prior studies (e.g., O'Brien, 1988; Mikhail et al., 1999; Ramnath et al., 2005), the most recent I/B/E/S consensus forecast prior to the earnings announcement is retained. The initial sample comprises 5,694 company-year observations. Notably, many companies listed on the ASX are not covered by I/B/E/S.

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[11] This study is interested in mimicking the I/B/E/S consensus forecast that is broadly available to users on a monthly basis, rather than in creating a superior consensus. The reconstruction of the I/B/E/S consensus is necessary as both the aggregated value of the consensus and the attributes of individual forecasts that comprise the consensus are required by the study.

[12] Earnings announcement dates are sourced from I/B/E/S between 1987 and 1992 because they are not available in the SIRCA database. Of the sample, observations with earnings announcement dates differing by more than one day between SIRCA and I/B/E/S are less than 10% of observations between 2003 and 2007, more than 10% but less than 20% of observations in 1999, 2000 and 2002, more than 20% but less than 30% of observations in 2001, and the discrepancies increase substantially before 1999 (between 1993 and 1998). Earnings announcement dates reported by I/B/E/S tend to be later than those reported by SIRCA. Earnings announcement dates reported in SIRCA tend to correspond with the ASX announcement dates wherever available on the ASX website.

[13] If a company is traded on multinational stock exchanges and followed by multinational analysts, only Australian analyst forecasts are included in the sample.

Company-year observations are eliminated if the actual earnings in I/B/E/S or the earnings announcement dates from SIRCA are missing. Because the consensus forecast is compared with the most recent forecast for a particular company and year, the most recent company-year individual analyst forecasts prior to the earnings announcement are extracted and matched from the Detail files. After observations with a mismatch of financial-year end between reported actual earnings and forecast earnings are excluded, 278 outliers are eliminated by omitting observations with price-deflated forecast error greater than 10 percent (Richardson et al., 2004; Clement and Tse, 2005). These observations are likely to be the result of a data entry error. Table 2.1 lists the sample selection criteria and their effects on the sample size. As shown in Table 2.1, the final annual earnings forecast sample yields 4,358 company-year observations, representing 862 unique companies.[14]

<Insert Table 2.1 about Here>

2.4.3 Sample Descriptive Statistics

Panel A of Table 2.2 reports the year-by-year sample descriptive statistics for all company-year observations. The number of companies followed by at least two analysts varies across years and ranges from a low of 21 companies in 1987 to a high of 357 companies in 2007. The number of companies covered generally increases towards the later years, reflecting the increased coverage of I/B/E/S for the Australian market. Companies in the sample have an average (median) market capitalization of \$2 (\$0.5) billion, reflecting the skewed distribution of companies covered by analysts. That is, analysts follow a limited number of very large companies. They also selectively cover small or medium size companies.

<Insert Table 2.2 about Here>

Panel A reports analyst coverage statistics. The average number of analyst forecasts included in the consensus is approximately seven. This is about one third of the

[14] As expected the sample reflects companies with analyst coverage and not all companies on the ASX are followed by analysts. The results must be interpreted with respect to this limitation.

number reported by Ke and Yu (2006) for U.S. analyst coverage statistics, due to relatively fewer brokerage firms and analysts providing company coverage in the Australian market.

Panel A also presents descriptive statistics for the distribution of timeliness of the consensus and the most recent forecast. Despite the last I/B/E/S consensus being published in the month prior to the earnings announcement, the median age of the consensus forecast is 96 calendar days before the earnings announcement. The median age of the most recent forecast is 21 calendar days. The most recent forecast is approximately 75 calendar days more recent than the median age of the consensus forecast, suggesting that the most recent forecast should be more accurate if new information has been incorporated into it.

The consensus in early years of the sample period, notably from 1987 to 1990, is on average 20 days staler than that in more recent years. The inclusion of stale forecasts in the consensus is likely to reduce its accuracy. In more recent years, the relative timeliness of consensus forecasts improves, consistent with previous findings (Barron and Stuerke, 1998; Brown, 2001; Ramnath et al., 2005).

Panels B and C present descriptive statistics for the company-year observations included in the ASX 100 Index and outside the ASX 100 Index, respectively. Partitioning the sample into the ASX 100 companies and companies outside the Index reduces the sample size to 3,004 observations because the constituent list for the ASX 100 Index is unavailable in SIRCA prior to fiscal 1997. The ASX 100 companies have higher market capitalization, are covered by more analysts, and their forecasts are updated in a more timely manner, as compared with companies outside the Index. The ASX 100 companies have an average (median) market capitalization of $6 ($2.7) billion and are followed by 10 analysts on average. The median age of the consensus (most recent) forecast for these companies is 86 (10) days. By comparison, companies outside the ASX 100 Index have an average (median) market capitalization of $0.4 ($0.3) billion and are covered by an average of five analysts.

The median age of the consensus (most recent) forecast for these companies is 103 (30) days. The ASX 100 companies and companies outside the Index show different company and forecast characteristics. These differences may have effects on forecast accuracy. Further analysis is conducted in Section 2.6.2.

Panel D presents the Pearson correlations among the variables. It indicates significant negative associations between *AFE* and *ANALYST*, *LNSIZE*, *ASX100* and *TACC*. The results suggest that the accuracy of analysts' forecasts increases with the number of analysts following, firm size, whether or not the company included in the ASX 100 Index, and the company's earnings management behaviour. The results also indicate a significant positive correlation between *AFE* and *PASTAFE*, suggesting that analysts' past forecast performance has a predictive power for their forecast accuracy. These company and analyst characteristics are included in the multivariate regression in Section 2.7.2 to control for the factors that may be associated with the accuracy of analysts' forecasts. As expected, *ASX100* is highly correlated with *ANALYST*, *TIMELINESS*, *LNSIZE*, indicating that the company included in the ASX 100 Index attracts more analyst following and has higher market capitalization. Analysts tend to issue more timely forecasts for these companies.

2.5 Evaluating Forecast Accuracy

2.5.1 Variable Definitions

The absolute forecast error is used to measure forecast accuracy:

$$AFE_{jts} = \left| A_{jt} - F_{jts} \right| / P_{j,\, t\text{-}1} \tag{1}$$

Following Richardson et al. (2004), the absolute forecast error AFE_{jts} is defined as the absolute value of the difference between A_{jt}, actual annual earnings per share (EPS) of company j in year t, and F_{jts}, the forecast EPS using each of the alternative forecast measures, s, and is deflated by company j's share price[15] 11 months before the earnings announcement month, $P_{j,\,t\text{-}1}$.[16]

Each of the alternative forecast measures, denoted by s, is one of the following: the mean consensus forecast (s = *mean*), the median consensus forecast (s = *median*) or the most recent forecast (s = *mr*). F_{jtmean}, the mean consensus forecast, is the mean of all the individual analyst forecasts available as at the publication date of the last I/B/E/S consensus before the earnings announcement for company j in year t. $F_{jtmedian}$, the median consensus forecast, is the median of all the individual analyst forecasts available as at the publication date of the last I/B/E/S consensus before the earnings announcement for company j in year t. F_{jtmr}, the most recent forecast, is the latest individual analyst forecast EPS reported to I/B/E/S before the earnings announcement for company j in year t.[17]

To compare the accuracy of the consensus and the most recent forecast for each year of the sample period, AFE_{jts} is computed to measure forecast accuracy at the company level for each year and then aggregate these results across companies.

$$MAFE_{ts} = \frac{1}{N}\sum_{j=1}^{N} AFE_{jts} \tag{2}$$

For each forecast measure, s, the mean of the AFE_{jts} in year t, $MAFE_{ts}$, is averaged across all available company observations (j = 1,…, N) in year t.

$$MAFE_{s} = \frac{1}{N}\sum_{n=1}^{N}\left\{\frac{1}{T}\sum_{t=1}^{T} AFE_{jts}\right\} \tag{3}$$

For each forecast measure, s, the pooled mean of the AFE_{jts}, $MAFE_{s}$, is averaged across years (t = 1,…, T) for each company j, and then averaged across companies to evaluate forecast accuracy at an aggregate level across years and companies.

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[15] Brown (1996) argues the share price is the appropriate deflator to use when valuing companies because the primary use of analysts' earnings forecasts for security analysis is to make investment decisions.

[16] For companies listed less than 11 months, their forecast errors are deflated by the first listed month closing share prices.

[17] Consistent with Bartov et al. (2002) and Brown and Caylor (2005), the average value of the analysts' forecasts is used if more than one analyst forecast is issued on the most recent day.

$MAFE_{ts}$ and $MAFE_s$ are calculated to compare the accuracy of each forecast measure for each year and overall for the sample period. Significance tests of the differences in accuracy are used to test whether the consensus is more accurate than the most recent forecast (H1).

The timeliness of the consensus forecast is measured by taking the average value of the timeliness of individual analyst forecasts included in the last consensus prior to the earnings announcement, where the timeliness of an individual analyst forecast is measured with reference to the number of calendar days between the date of the individual analyst forecast issued prior to the earnings announcement and the earnings announcement date. The timeliness of the most recent forecast is measured with reference to the number of calendar days between the date of the most recent forecast issued prior to the earnings announcement and the earnings announcement date. The number of analysts following is either the number of analysts contributing to the consensus forecast or one for the most recent forecast.

2.5.2 Forecast Accuracy and Pairwise Differences in Forecast Accuracy

Table 2.3 reports the accuracy of the mean consensus, the median consensus and the most recent forecast. The forecast accuracy is measured by the mean of the absolute forecast errors across all available company-year observations for the year. For the 1987–1990 period, the most recent forecast is more accurate than the consensus forecast. By comparison, O'Brien (1988)'s 1975–1981 sample and Brown (1991)'s 1984–1988 sample show similar effects. In the more recent period from 1991 to 2007, the results suggest that both the mean and median consensus forecasts are more accurate than the most recent forecast. The accuracy of the median (mean) consensus forecast outperforms that of the most recent forecast in 15 (13) out of these 17 most recent years. The accuracy of the median consensus is greater than the mean consensus in 18 out of a total of 21 years.

<Insert Table 2.3 about Here>

Table 2.3 also reports the results of statistical tests for differences in accuracy among the mean consensus, the median consensus and the most recent forecast. A negative sign on a *t*-statistic indicates that the first of the pair of forecast measures compared is more accurate. For example, in the fiscal year 2007, the *t*-statistic for the pairwise test of differences in accuracy between the median consensus and the most recent forecast is -4.72, which favours the median consensus, and is statistically significant at the 0.01 level. The results confirm that whilst in the late 1980s the most recent forecast is significantly more accurate than the consensus, the consensus forecast outperforms the most recent forecast in more recent years. The results show that the median (mean) consensus forecast dominates the most recent forecast where significant differences exist for 9 (6) out of these 15 years.[18]

In terms of economic significance, Table 2.3 shows that the most recent forecast is on average less accurate than the consensus by 0.09% of share price.[19] For a company with a market capitalization of $2 billion, the average market capitalization in the sample, this translates into a most recent forecast that misses actual earnings by $1.8 million relative to the consensus forecast.[20]

Based on the results of Table 2.2 and Table 2.3, it seems plausible that two effects influence the accuracy of analysts' forecasts. The first, which reflects a time series phenomenon, arises from the decline in average horizon difference for consensus and the most recent forecasts, and leads to the improved relative accuracy for consensus forecasts. The second, a cross-sectional phenomenon, arises from firms that grow and attract more analyst coverage, leading to an improvement in analysts' forecast accuracy.

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[18] The qualitative results remain unchanged when signed forecast errors are used to measure forecast accuracy.
[19] The difference between the average AFE for the most recent forecast (0.885%) and the average AFE for the median consensus (0.975%) for the full sample is 0.09% of share price.
[20] The average market capitalisation ($2 billion) multiplies by 0.09% is $1.8 million.

2.6 Explanations for the Greater Accuracy of Consensus Forecasts

Following Ramnath et al. (2005), this study examines whether the number of analysts following and the timeliness of analysts' forecasts explain the relative greater forecast accuracy of consensus forecasts using a cross-sectional regression (H2).

2.6.1 Cross-sectional Regression

$$AFE_{jts} = \beta_0 + \beta_1(MEASURE_{jts}) + \beta_2(ANALYST_{jts}) + \beta_3(TIMELINESS_{jts}) + \varepsilon_{jts} \quad (4)$$

Where:

AFE_{jts}: is the absolute value of the median consensus (s = *median*) or the most recent (s = *mr*) forecast error deflated by share price 11 months before the earnings announcement month for company *j*'s annual EPS in year *t*;[21]

$MEASURE_{jts}$: is an indicator variable, coded one if AFE is sourced from the median consensus forecast (s = *median*); coded zero if AFE is sourced from the most recent forecast (s = *mr*) for company *j* in year *t*;

$ANALYST_{jts}$: equals the number of analysts contributing to the consensus forecast (s = *median*) or one for the most recent forecast (s = *mr*) for company *j* in year *t*;

$TIMELINESS_{jts}$: equals the average value of the timeliness of individual analyst forecasts included in the last consensus prior to the earnings announcement, where the timeliness of an individual analyst forecast is measured by the number of calendar days between the date of the individual analyst forecast issued prior to the earnings

[21] The same conclusion is reached if the mean consensus forecast is used.

announcement and the earnings announcement date for the median consensus forecast (s = *median*) or the number of calendar days between the date of the most recent forecast issued prior to the earnings announcement and the earnings announcement date for the most recent forecast (s = *mr*) for company j in year t.

Cross-sectional regression is estimated for each year t respectively and the mean of the annual coefficient estimates across the sample period is calculated.

Prior research demonstrates that the more analysts following, the greater is the accuracy of consensus forecasts. The absolute forecast error is expected to decrease as the number of analysts following increases, $\beta_2 < 0$. Increasing forecast accuracy is also associated with the timeliness of analysts' forecasts. The accuracy of analysts' forecasts improves when the earnings announcement date approaches. Hence, the absolute forecast error is expected to decrease as the timeliness of analysts' forecasts is shorter, $\beta_3 > 0$, for the regression model (4).

Consistent with Ramnath et al. (2005) and Ke and Yu (2006), company-specific and macroeconomic control variables are not included in the model. This may seem unusual but the model examines determinants of the relative accuracy between the consensus and the most recent forecast given the underlying economic conditions. Both forecast measures are exposed to the same company-specific factors and macroeconomic effects.

Because the aggregation value of consensus forecasts is expected to outweigh the timing advantage of the most recent forecast, the forecasting superiority of the consensus forecast over the most recent forecast is expected to be reduced after controlling for the forecast aggregation and timing. In other words, the most recent forecast would outperform the consensus forecast after controlling for these factors. β_1, the coefficient on the *MEASURE* indicator variable, measuring the difference in accuracy of the consensus forecast versus the most recent forecast, is expected to be positive (i.e., the consensus forecast generates larger absolute forecast errors than the most recent forecast), β_1>0. β_0, the intercept, is expected to be positive, β_0>0, since the absolute forecast error is greater than or equal to zero. Cross-sectional regression is estimated for each year *t* respectively. Coefficient estimates are presented as the mean across the sample period following the Fama-MacBeth (1973) procedure. The *t*-statistics and significance levels are obtained under the null that the mean of the coefficient distributions across the sample period equals zero.

To control for size effects on forecast accuracy, the sample is partitioned into observations included in the ASX 100 Index and outside the Index to examine whether the same factors are associated with the greater accuracy of consensus forecasts for these two groups.

2.6.2 Regression Results

Table 2.4 reports the results of the regression model that examines whether the number of analysts following and the timeliness of analysts' forecasts explain the greater accuracy of consensus forecasts for the overall sample periods, pre-1991 and post-1991, and observations included in the ASX 100 Index and outside the Index. For the overall sample period, consistent with Hypothesis 2, the coefficient on number of analysts following is significantly negative (-0.0788, t = -6.28), indicating forecast accuracy increases with the number of analysts following. The coefficient on the timeliness of analysts' forecasts is close to zero (0.0004) and is not statistically significant. It indicates that the timeliness of analysts' forecasts does not contribute to increasing forecast accuracy. The coefficient on the *MEASURE* indicator variable that measures the difference in accuracy of the consensus forecast (coded one) versus the most recent forecast (coded zero) is significant and positive (0.3284, t = 6.34), after controlling for forecast aggregation and timing. It indicates that the consensus forecast generates larger absolute forecast errors and is less accurate than the most recent forecast after controlling for the effects of the number of analysts following and the timeliness of analysts' forecasts. It suggests that the aggregation value of the consensus forecast outweighs the timing advantage of the most recent forecast, and the number of analysts following largely explains the forecasting superiority of the consensus forecast. The model's explanatory power is low (R^2 = 1.98%), but consistent with previous findings (Ramnath et al., 2005). The results from the post-1991 period are consistent with the results for the overall sample period.

<Insert Table 2.4 about Here>

Both sets of regression results for the ASX 100 companies and companies outside the Index show that the aggregating value of the consensus outweighs the timing advantage of the most recent forecast. The coefficients on number of analysts following for both subsamples are significantly negative (-0.0586, t = -3.80 for the ASX 100 companies; -0.1154, t = -8.94 for companies outside the Index). The association between forecast accuracy and the number of analysts following is stronger for the companies outside the ASX 100 Index because these companies are usually covered by fewer analysts as compared to the ASX 100 companies. The incremental analyst coverage more effectively purges the individual analyst's idiosyncratic error.

Overall, the results suggest that the consensus forecast is more accurate than the most recent forecast. The forecast superiority of the consensus forecast can be attributed to the aggregating value of the consensus forecast outweighing the timing advantage of the most recent forecast. These results show that the greater accuracy of the consensus forecast is due to the number of analysts following and contributing to the consensus. The results are robust to using the mean consensus rather than the median consensus, constructed by using individual analyst forecasts. They are also robust to using the I/B/E/S summary consensus measure.

2.7 Robustness Checks

2.7.1 Excluding the Most Recent Forecast from the Consensus

If the most recent forecast is issued before the formation date of the last consensus prior to the earnings announcement, it will be included in the calculation of the consensus forecast. In the final sample, 2,888 observations (66% of total observations) have the most recent forecast included in the consensus for the corresponding company-year. Given this, the question arises whether the relative timeliness of the consensus is attributable to its increasing accuracy together with its aggregation value. In this section, the relative accuracy between the consensus and the most recent forecast is re-examined using a subsample which excludes the most recent forecast from the calculation of the consensus.

Column (1) of Table 2.5 repeats the analysis in Table 2.4. The control variables for the number of analysts following and timeliness are the same as those described in the regression model (4). The descriptive statistics (not tabulated) show that the median age of the consensus excluding the most recent forecast is 104 calendar days before the earnings announcement, suggesting that timeliness of consensus forecasts is improved by including recently-updated forecasts.

The results in Column (1) of Table 2.5 are similar to those in Table 2.4. It shows that the coefficient on number of analysts following is negative and statistically significant, whereas the coefficient on the timeliness of analysts' forecasts is close to zero and statistically insignificant. It indicates that the number of analysts following explains the consensus forecasting advantage. The results demonstrate that, conditional on the relative timeliness of consensus forecasts, there are gains in accuracy from aggregating to reduce idiosyncratic error.

<Insert Table 2.5 Here>

2.7.2 *Controlling for Company and Analyst Characteristics*

Consistent with Ramnath et al. (2005) and Ke and Yu (2006), company-specific variables are not included in the model when comparing the accuracy of the two forecast measures. That is, the basic model compares the accuracy of the two measures irrespective of the source of the differences in accuracy. To ensure the results are robust to the inclusion of other factors associated with the accuracy of analysts' forecasts, an additional set of variables is included in the analysis: past forecast accuracy, firm size, whether or not the company observation is included in the ASX 100 Index, and the level of accruals. Lim (2001) and Brown (2001b) show that the accuracy of analysts' forecasts is significantly positively correlated with their past forecast accuracy. Brown (2001b) suggests that analysts' past forecasting performance has a greater predictive power for forecast accuracy than all other analyst characteristics combined. Accordingly a control for past forecast accuracy to proxy for analyst characteristics is included. Since high reputation analysts provide more accurate and timely forecasts and have a greater impact on share prices (Stickel, 1992; Brown et al., 2007), past forecast accuracy is also used to proxy for the reputation of analysts. Brown et al. (1999) and Lim (2001) find that firm size is negatively related to analysts' forecast errors, indicating that the general information environment is likely to be richer for large companies resulting in analysts issuing more accurate forecasts for them. An indicator variable to control for the possible different information environment for companies included in the ASX 100 Index as compared to companies outside the Index is also incorporated (Chan et al., 2006; Brown et al., 2007). Company's earnings management behaviour may affect the quality of the reported earnings and hence the accuracy of analysts' forecasts. Since managers perceive analysts as one of the most important groups influencing the share price of their companies (Graham et al., 2005), they could use accruals, or issue management earnings guidance to manage earnings in an attempt to meet or beat analysts' forecasts (Habib and Hossain, 2008). For robustness, a control for total accruals as a proxy for the quality of the reported earnings is incorporated into the regression.

Imposing the requirement that past forecast data, the constituent list for the ASX 100 Index, and accruals data are all available reduces the sample size to 2,346 observations. Consistent with prior research, Column (2) of Table 2.5 illustrates that the accuracy of analysts' forecasts is significantly positively correlated with their past forecast accuracy and increases with firm size. Although it lies in the opposite direction to the predicted sign and is statistically insignificant, the coefficient on index is significantly negative after the firm size is dropped from the regression (not tabulated). It indicates that firm size and the index are highly correlated. The accuracy of Analysts' forecasts is significantly negatively correlated with total accruals, suggesting that earnings management has an effect on the forecast accuracy. Adjusted R-square increases to 11%. The results remain robust to the inclusion of additional sets of variables. That is, the number of analysts following continues to explain the greater accuracy of the consensus forecast.

2.8 Conclusion

This study provides direct evidence of the accuracy of the consensus forecast versus the most recent forecast, as measures of the market's earnings expectations prior to earnings announcements in the Australian market by examining 4,358 company-year annual analyst forecasts between 1987 and 2007. The results suggest that in the late 1980s there is some evidence that the most recent forecast is more accurate than the consensus. This is consistent with U.S. evidence (O'Brien, 1988; Brown, 1991). However, the results in more recent years show that the consensus forecast is more accurate than the most recent forecast. For the sample period from 1991 to 2007, the accuracy of the consensus forecast consistently outperforms that of the most recent forecast in 15 out of these 17 years. Statistically significant differences are shown in 9 out of those 15 years. This supports the findings reported by recent U.S. studies (Barron and Stuerke, 1998; Brown, 2001; Ramnath et al., 2005) and is consistent with the improving timeliness of forecasts included in consensus forecasts. The forecasting superiority of the consensus forecast can be attributed to the number of analysts following and contributing to the consensus. The aggregation value of the consensus outweighs the small timing advantage of the most recent forecast over the short forecast horizon examined in this study.

This study contributes to prior research on Australian analysts' forecasts by providing evidence on the importance of diversifying idiosyncratic individual error across analyst forecasts in the consensus forecast, in a non-U.S. setting with relatively thin analyst coverage and a different disclosure environment. It also supports market practitioners' views, as evidenced by press reports, that the consensus forecast is a better measure of the market's earnings expectations.

Future research could examine how analysts change their forecasting behaviour to maintain their forecast accuracy in an environment of increased regulation over the dissemination of company information. Future research might also profitably consider whether consensus forecasts can be improved by forming a consensus based on forecasts of a subset of highly skilled analysts or analysts possessing certain attributes.

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Table 2.1
Sample Selection

	Number of company-year observations remaining in sample	Percentage of total consensus forecasts
Consensus forecasts from 1987 to 2007 for Australian companies with at least 2 analysts following	5,694	100%
Actual earnings (from I/B/E/S) and earnings announcement date (from SIRCA) available	4,650	82%
Excluding companies with change in financial year-end	4,636	81%
Excluding outliers = Final sample (862 unique companies)	4,358	77%

Notes:
Consensus forecasts are the means or medians of all the individual analyst forecasts available as at the publication date of the last I/B/E/S consensus before earnings announcement. Individual analyst forecasts are extracted from the I/B/E/S Detail History files. Outliers are defined as the observations where absolute forecast errors are greater than 10%.

Table 2.2
Descriptive Statistics

Panel A: Descriptive statistics for all company-year observations in the sample

Fiscal Year	Number of firms followed	Market capitalization ($000)		Mean or Median consensus								Most recent			
				Number of analysts following				Calendar days between forecast issue date and earnings announcement date				Calendar days between forecast issue date and earnings announcement date			
		Mean	Median	Mean	25%	Median	75%	Mean	25%	Median	75%	Mean	25%	Median	75%
1987	21	314,099	95,034	4	2	3	5	121	89	124	143	57	25	41	79
1988	67	525,365	203,467	6	2	4	10	141	97	145	178	56	22	37	71
1989	135	902,876	330,714	8	4	7	11	100	75	97	123	30	17	26	30
1990	109	1,258,604	517,294	8	5	8	11	128	96	130	155	37	20	33	50
1991	119	1,071,798	332,952	7	3	7	10	89	57	88	117	24	14	20	28
1992	136	1,211,646	371,578	6	3	5	8	95	75	94	117	32	18	28	36
1993	150	1,173,040	419,064	8	4	8	12	103	73	102	130	25	6	14	28
1994	167	1,478,210	483,724	7	3	6	10	102	78	99	129	23	6	12	34
1995	227	1,094,674	325,229	7	3	6	11	82	57	76	100	31	7	21	41
1996	223	1,239,120	368,646	7	3	6	10	86	55	82	110	21	5	11	23
1997	248	1,277,200	371,632	7	4	7	11	91	64	92	116	27	6	14	36
1998	272	1,597,276	385,870	8	4	7	12	86	60	85	103	26	5	16	37
1999	279	1,630,780	355,000	8	4	7	11	98	65	96	123	33	7	21	39
2000	286	1,820,866	460,091	7	4	6	10	105	76	100	128	35	8	21	49
2001	273	2,226,858	410,793	8	4	8	11	113	78	105	141	39	7	20	57
2002	234	2,516,359	518,125	7	4	7	10	112	78	110	138	36	8	21	48
2003	237	2,381,173	594,243	6	3	6	9	84	58	76	104	28	6	16	38
2004	255	2,500,386	611,102	6	3	6	9	104	70	99	131	39	8	22	46
2005	274	2,930,005	740,161	5	3	5	7	111	58	98	148	40	8	23	54
2006	289	3,538,086	924,252	6	3	5	8	111	60	105	146	46	12	28	52
2007	357	3,338,790	698,589	6	3	5	9	114	74	110	151	47	14	29	65
All years	4,358	1,992,603	465,252	7	3	6	10	102	67	96	129	34	8	21	43

Table 2.2 – Continued

Descriptive Statistics

Panel B: Descriptive statistics for the company-year observations in the ASX 100 Index

Fiscal Year	Number of firms followed	Market capitalization ($000)		Mean or Median consensus								Most recent			
				Number of analysts following				Calendar days between forecast issue date and earnings announcement date				Calendar days between forecast issue date and earnings announcement date			
		Mean	Median	Mean	25%	Median	75%	Mean	25%	Median	75%	Mean	25%	Median	75%
1997	94	2,953,636	1,423,634	11	10	12	13	85	55	83	112	13	5	8	15
1998	98	3,956,009	1,989,377	12	10	13	16	76	55	81	96	12	2	8	17
1999	99	4,153,406	1,669,040	11	9	12	14	87	61	85	110	18	3	10	26
2000	100	4,590,157	2,051,867	11	8	11	13	91	68	89	111	14	4	9	20
2001	89	6,161,537	2,029,347	12	10	12	13	92	66	93	113	13	4	8	18
2002	92	5,831,771	2,439,551	11	9	11	13	97	65	96	119	15	2	10	20
2003	92	5,514,585	2,473,097	9	8	9	10	76	55	71	89	14	3	9	23
2004	94	5,937,732	2,770,794	9	8	9	11	95	70	94	114	15	3	8	21
2005	92	7,547,484	4,135,185	7	6	7	9	98	48	80	131	21	5	13	32
2006	98	8,877,167	4,559,908	8	7	9	10	102	58	89	130	26	6	15	30
2007	98	10,444,41	4,964,323	10	7	10	12	111	67	107	147	26	7	17	36
All years	1,046	5,997,902	2,673,730	10	8	10	13	92	60	86	116	17	4	10	23

Table 2.2 – Continued

Descriptive Statistics

Panel C: Descriptive statistics for the company-year observations outside the ASX 100 Index

Fiscal Year	Number of firms followed	Market capitalization ($000)		Mean or Median consensus								Most recent			
				Number of analysts following				Calendar days between forecast issue date and earnings announcement date				Calendar days between forecast issue date and earnings announcement date			
		Mean	Median	Mean	25%	Median	75%	Mean	25%	Median	75%	Mean	25%	Median	75%
1997	154	253,921	199,334	5	3	4	7	95	67	95	119	35	8	22	54
1998	174	268,793	226,777	6	3	5	8	91	62	89	109	34	10	24	49
1999	180	243,336	170,697	6	3	5	8	105	73	103	133	41	13	28	47
2000	186	332,000	235,979	5	3	4	7	113	83	108	140	47	13	33	64
2001	184	323,671	211,179	6	3	5	8	122	86	118	154	52	14	33	76
2002	142	368,346	223,893	5	3	4	7	122	89	119	142	49	16	33	65
2003	145	393,076	235,352	4	2	4	6	89	60	82	113	37	9	22	51
2004	161	493,488	319,983	4	2	4	6	109	71	102	149	53	16	34	66
2005	182	595,895	361,891	4	2	3	6	118	68	106	152	49	10	32	66
2006	191	798,663	437,388	5	2	4	6	116	65	113	155	57	19	36	72
2007	259	650,176	393,403	5	2	4	7	116	76	112	153	54	17	36	77
All years	1,958	443,885	270,099	5	3	4	7	109	72	103	139	47	13	30	62

Notes:
This table reports descriptive statistics for the distribution of company-year observations included in the sample. Panel A presents descriptive statistics for all company-year observations. Panel B presents descriptive statistics for the company-year observations included in the ASX 100 Index. Panel C presents descriptive statistics for the company-year observations outside the ASX 100 Index. Analyst forecast data is obtained from I/B/E/S. Average market capitalization is the equity value 11 months before the company's earnings announcement month. The number of analysts following equals either the number of analysts contributing to the I/B/E/S consensus forecast or one for the most recent forecast.

Table 2.2 – Continued
Pearson Correlation Matrix

Panel D: Pearson Correlation Matrix for the sample including additional variables

	AFE	*MEASURE*	*ANALYST*	*TIMELINESS*	*PASTAFE*	*LNSIZE*	*ASX100*	*TACC*
AFE	1							
MEASURE	-0.038**	1						
ANALYST	-0.111***	0.782***	1					
TIMELINESS	-0.020	0.625***	0.394***	1				
PASTAFE	0.257***	-0.040**	-0.113***	-0.001	1			
LNSIZE	-0.221***	0	0.282***	-0.195***	-0.163***	1		
ASX100	-0.151***	0	0.271***	-0.199***	-0.143***	0.756***	1	
TACC	-0.091***	0	-0.022	0.056***	-0.085***	0.054***	0.002	1

Notes:
Panel D presents the Pearson correlation matrix for the sample including additional variables: past forecast accuracy, firm size, whether the company observation is included in the ASX 100 Index, and the level of accruals. AFE_{jts} is the absolute value of the median consensus (s = *median*) or the most recent (s = *mr)* forecast error deflated by share price 11 months before the earnings announcement month for company *j*'s annual EPS in year *t.* This variable is multiplied by 100, so the coefficient estimates are as a percentage of share price. $MEASURE_{jts}$ is an indicator variable, coded one if AFE is sourced from the median consensus forecast (s = *median*); coded zero if AFE is sourced from the most recent forecast (s = *mr*) for company *j* in year *t*. $ANALYST_{jts}$ equals the number of analysts contributing to the consensus forecast (s = *median*) or one for the most recent forecast (s = *mr*) for company *j* in year *t*. $TIMELINESS_{jts}$ equals the average value of the timeliness of individual analyst forecasts included in the last consensus prior to the earnings announcement, where the timeliness of an individual analyst forecast is measured by the number of calendar days between the date of the individual analyst forecast issued prior to the earnings announcement and the earnings announcement date for the median consensus forecast (s = *median*) or the number of calendar days between the date of the most recent forecast issued prior to the earnings announcement and the earnings announcement date for the most recent forecast (s = *mr)* for company *j* in year *t*. $PASTAFE_{jts}$ is the absolute forecast error AFE_{jts} for the prior year. $LNSIZE_{jts}$ is the log market capitalization 11 months before the earnings announcement month for company *j* in year *t*. $ASX100_{jts}$ is an indicator variable, coded one if company *j* is included in the ASX100 Index; coded zero if company is outside the ASX100 Index in year *t*; $TACC_{jts}$ equals the difference between net income and cash flow from operations for company *j* in year *t*.

Table 2.3
Accuracy of the Consensus and the Most Recent Earnings Forecasts by Year

Fiscal Year	Number of company-year observations	Average AFE (%)			*t*-statistic for pairwise test of differences		
		Mean consensus	Median consensus	Most recent	Mean – Median	Mean – Most recent	Median – Most recent
1987	21	1.712	1.684	1.398	0.25	0.57	0.53
1988	67	1.425	1.246	0.816	2.22**	2.58**	1.79*
1989	135	1.092	0.950	0.891	2.87***	1.82*	0.53
1990	109	1.156	0.958	0.695	2.39**	2.74***	1.66*
1991	119	0.937	0.594	0.822	3.84***	0.88	-2.02**
1992	136	0.984	0.976	1.179	0.19	-1.88*	-1.98**
1993	150	0.866	0.824	0.953	1.62	-0.97	-1.47
1994	167	0.713	0.687	0.763	1.68*	-0.74	-1.21
1995	227	0.823	0.803	0.882	1.42	-1.05	-1.37
1996	223	0.768	0.730	0.709	2.02**	1.07	0.38
1997	248	0.655	0.674	0.776	-0.80	-3.06***	-3.01***
1998	272	0.798	0.741	0.793	2.26**	0.09	-0.84
1999	279	0.988	0.980	0.949	0.34	0.70	0.58
2000	286	1.177	1.181	1.207	-0.24	-0.55	-0.47
2001	273	1.335	1.330	1.422	0.29	-1.40	-1.57
2002	234	1.040	1.032	1.210	0.32	-2.67***	-2.66***
2003	237	0.987	1.020	1.155	-1.76*	-2.48**	-2.00**
2004	255	0.893	0.824	0.980	2.00**	-1.41	-2.72***
2005	274	0.851	0.820	0.991	1.51	-2.25**	-2.66***
2006	289	0.742	0.706	0.819	1.48	-1.50	-2.21**
2007	357	0.766	0.711	1.009	2.65***	-4.08***	-4.72***
All years	4,358	0.927	0.885	0.975	6.39***	-2.99***	-5.68***

Notes:
Forecast accuracy is measured by the absolute forecast error (AFE). AFE is defined as the absolute value of the difference between actual EPS and the forecast EPS deflated by share price 11 months before the earnings announcement month. Average AFE is the mean of the AFEs across all available company-year observations for the year. The mean consensus is the mean of all the individual analyst forecasts available as at the publication date of the last I/B/E/S consensus before the earnings announcement. The median consensus is the median of all the individual analyst forecasts available as at the publication date of the last I/B/E/S consensus before the earnings announcement. The most recent forecast is the latest individual analyst forecast EPS reported to I/B/E/S prior to the announcement of actual earnings. The *t*-statistic is a test of the pairwise difference in accuracy between the consensus and the most recent forecasts. A negative sign on a *t*-statistic in this table indicates that the first of the pair of forecast measures compared is more accurate. The converse is true for a positive sign. *Statistical significance at the 0.10 level, two-tail test. **Statistical significance at the 0.05 level, two-tail test. ***Statistical significance at the 0.01 level, two-tail test.

Table 2.4
Association between the Number of Analysts Following and the Greater Forecast Accuracy of the Consensus Forecast

$AFE_{jts} = \beta_0 + \beta_1(MEASURE_{jts}) + \beta_2(ANALYST_{jts}) + \beta_3(TIMELINESS_{jts}) + \varepsilon_{jts}$

Variable	*Predicted sign*	*AFE*				
		Overall period	*Pre-1991 period*	*Post-1991 period*	*ASX 100*	*Outside ASX 100*
Intercept	+	1.0290***	0.8807***	1.0588***	0.7861***	1.3636***
		(20.65)	(5.29)	(22.55)	(12.20)	(21.42)
MEASURE	+	0.3284***	0.3619	0.3205***	0.6669***	0.3521***
		(6.34)	(2.24)	(5.89)	(4.29)	(6.85)
ANALYST	–	-0.0788***	-0.0889	-0.0765***	-0.0586***	-0.1154***
		(-6.28)	(-1.50)	(-8.19)	(-3.80)	(-8.94)
TIMELINESS	+	0.0004	0.0028	-0.0001	-0.003 **	-0.0008
		(0.76)	(1.29)	(-0.25)	(-2.84)	(-1.08)
Number of observations		4,358	332	4,026	1,046	1,958
Adjusted R^2		1.98%	1.01%	2.2%	2.18%	1.90%

Notes:
AFE_{jts} is the absolute value of the median consensus (s = *median*) or the most recent (s = *mr)* forecast error deflated by share price 11 months before the earnings announcement month for company *j*'s annual EPS in year *t.* This variable is multiplied by 100, so the coefficient estimates are as a percentage of share price. $MEASURE_{jts}$ is an indicator variable, coded one if AFE is sourced from the median consensus forecast (s = *median*); coded zero if AFE is sourced from the most recent forecast (s = *mr*) for company *j* in year *t*. $ANALYST_{jts}$ equals the number of analysts contributing to the consensus forecast (s = *median*) or one for the most recent forecast (s = *mr*) for company *j* in year *t*. $TIMELINESS_{jts}$ equals the average value of the timeliness of individual analyst forecasts included in the last consensus prior to the earnings announcement, where the timeliness of an individual analyst forecast is measured by the number of calendar days between the date of the individual analyst forecast issued prior to the earnings announcement and the earnings announcement date for the median consensus forecast (s = *median*) or the number of calendar days between the date of the most recent forecast issued prior to the earnings announcement and the earnings announcement date for the most recent forecast (s = *mr)* for company *j* in year *t*. The regression is estimated for each year *t*, respectively. Coefficient estimates are presented as the mean across the sample period following the Fama-MacBeth (1973) procedure. *Statistical significance at the 0.10 level, two-tail test. **Statistical significance at the 0.05 level, two-tail test. ***Statistical significance at the 0.01 level, two-tail test.

Table 2.5
Association between the Number of Analysts Following and the Greater Forecast Accuracy of the Consensus Forecast

$AFE_{jts} = \beta_0 + \beta_1(MEASURE_{jts}) + \beta_2(ANALYST_{jts}) + \beta_3(TIMELINESS_{jts}) + \varepsilon_{jts}$ (1)

for the subsample excluding the most recent forecast from the calculation of the consensus.

$AFE_{jts} = \beta_0 + \beta_1(MEASURE_{jts}) + \beta_2(ANALYST_{jts}) + \beta_3(TIMELINESS_{jts}) + \beta_4(PASTAFE_{jts}) + \beta_5(LNSIZE_{jts}) + \beta_6(ASX100_{jts}) + \beta_7(TACC_{jts}) + \varepsilon_{jts}$ (2)

for the subsample including additional variables: past forecast accuracy, firm size, whether the company observation is included in the ASX 100 Index, and the level of accruals.

Variable	*Predicted sign*	*AFE*	
		(1)	(2)
Intercept	+	0.9797***	4.3494***
		(21.81)	(6.42)
MEASURE	+	0.4127***	0.1610**
		(4.27)	(2.28)
ANALYST	–	-0.0775***	-0.0247***
		(-6.71)	(-3.44)
TIMELINESS	+	-0.0003	-0.0013*
		(-0.29)	(-1.91)
PASTAFE	+		23.3971***
			(7.06)
LNSIZE	–		-0.1802***
			(-5.35)
ASX100	–		0.1264
			(1.67)
TACC	–		-0.8971***
			(-3.52)
Number of observations		3,766	2,346
Adjusted R^2		2.35%	11.44%

Notes:
AFE_{jts} is the absolute value of the median consensus (*s = median*) or the most recent (*s = mr)* forecast error deflated by share price 11 months before the earnings announcement month for company *j*'s annual EPS in year *t.* This variable is multiplied by 100, so the coefficient estimates are as a percentage of share price. $MEASURE_{jts}$ is an indicator variable, coded one if AFE is sourced from the median consensus forecast (*s = median*); coded zero if AFE is sourced from the most recent forecast (*s = mr*) for company *j* in year *t*. $ANALYST_{jts}$ equals the number of analysts contributing to the consensus forecast (*s = median*) or one for the most recent forecast (*s = mr*) for company *j* in year *t*. $TIMELINESS_{jts}$ equals the average value of the timeliness of individual analyst forecasts included in the last consensus prior to the earnings announcement, where the timeliness of an individual analyst forecast is measured by the number of calendar days between the date of the individual analyst forecast issued prior to the earnings announcement and the earnings announcement date for the median consensus forecast (*s = median*) or the number of calendar days between the date of the most recent forecast issued prior to the earnings announcement and the earnings announcement date for the most recent forecast (*s = mr)* for company *j* in year *t*. $PASTAFE_{jts}$ is the absolute forecast error AFE_{jts} for the prior year. $LNSIZE_{jts}$ is the log market capitalization 11 months before the earnings announcement month for company *j* in year *t*. $ASX100_{jts}$ is an indicator variable, coded one if company *j* is included in the ASX100 Index; coded zero if company is outside the ASX100 Index in year *t*; $TACC_{jts}$ equals the difference between net income and cash flow from operations for company *j* in year *t*. The regression is estimated for each year *t*, respectively. Coefficient estimates are presented as the mean across the sample period following the Fama-MacBeth (1973) procedure. *Statistical significance at the 0.10 level, two-tail test. **Statistical significance at the 0.05 level, two-tail test. ***Statistical significance at the 0.01 level, two-tail test.

3 CHAPTER THREE

Exploration Intensity, Analysts' Private Information Development and Their Forecast Performance

3.1 Introduction

Investing in extractive companies can yield phenomenal returns upon successful mineral or oil and gas discovery (How, 2000; Kreuzer et al., 2007), but presents investors with several challenges, including pronounced information asymmetry and difficulty interpreting information that is publicly disclosed, especially regarding the prospective outcomes of exploration and evaluation (E&E) activities. For example, Poskitt (2005) reports that the share prices of extractive companies are highly sensitive to changes in the probability of discovering an economic mineral or oil and gas deposit. Ferguson and Crockett (2003) and Bird et al. (2013) conclude that investors who have little geological expertise may rely more on media reports or exploration announcements with positive adjectives because of the complexity of geological information.[22] As a result of high information asymmetry and the complexity of non-financial information, investors in the extractive industries may have a greater demand for analysts' information because of the key role played by analysts in searching for and processing information about firms and disseminating that information to investors. This study examines whether financial analysts who act

[22] Ferguson and Crockett (2003, p. 103) point out that in routine mining company disclosures, "discussion of complex variables such as metal purity, the width of the drilling intercepts, and the depth below the surface where the intercept occurs" are included. "Highly technical factors including the geochemical composition of the mineralization of the discovery" and "other complexities" could also be added.

as information intermediaries can help reduce this information asymmetry and whether their forecast performance is related to the intensity of E&E activities.

This study uses analysts' forecast accuracy as a proxy for the quality and usefulness of their research, that is, their forecast performance. Those analysts who have specialized knowledge in geological science and engineering, will be able to better understand and interpret the publicly available information, on the future prospects of E&E activities and their implications for future earnings. Their specialised knowledge will also be reflected in their forecasting and valuation models, enabling them to provide earnings forecasts that are likely to be more valuable to investors. I argue that when the intensity of E&E activities is higher and their future prospects are more uncertain, investors will demand earnings forecasts containing more such private information from analysts.[23] Investor demand provides strong incentives for analysts to acquire and develop more private information, which in turn enhances the overall information environment (Lang et al., 2003). At the same time, as the degree to which individual analysts' forecasts contain private information increases, the idiosyncratic portion of each individual forecast error also increases. Analysts' average forecasts are, however, improved because relatively more of these idiosyncratic forecast errors are averaged out through the aggregation process (Barron et al., 1998).[24]

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[23] Private information refers to information about future earnings that is developed by the individual, arising from analysts' information processing skills and different forecast modelling techniques, as opposed to common information that is known to all analysts (Barron et al., 1998). An example of private information acquisition and processing is analysts' site visits to extractive companies' operations and exploration grounds: on 28 October 2008, the *Australian Financial Review* (p. 21) reports that "analysts will visit Olympic Dam on the last day of a week-long tour of BHP's operations, which began yesterday with a trip to Karratha in the Pilbara and briefings on the company's iron ore and petroleum divisions. Today they travel south to take in the company's nickel operations at Mount Keith and the troubled Ravensthorpe plant, before heading to South Australia on Thursday." Using their specialized knowledge, analysts evaluate future prospects of these E&E activities and provide guidance to investors. For example, analysts from Citigroup said that the share price of Energy Resources of Australia (ERA) could rise almost 70 per cent to hit the target price of $23.30 a share set by the brokerage house if ERA's project hurdles could be cleared following a recent visit to the company's Ranger mine in the Northern Territory (*Australian Financial Review*, 30 June 2010, p. 26).

[24] Analysts' average (mean or median) forecast also refers to analysts' consensus forecast. This paper uses the term "analysts' average forecast" as opposed to "analysts' consensus forecast" to avoid confusion regarding the use of the analyst consensus construct developed by Barron et al. (1998) to measure the ratio of analysts' common information to their total information.

This study focuses on Australia because there are strong incentives for analysts in Australia to develop expertise in the extractive industries. The Australian economy is characterized by a high proportion of resource-based companies (Wu et al., 2010), and the Australian Securities Exchange (ASX) is one of the world's leading markets for mining and oil and gas financing.[25] Some of the world's largest diversified resource companies, including BHP Billiton and Rio Tinto, as well as many mid-tier and junior exploration companies are listed on the ASX. Furthermore, both pre- and post-IFRS Australian GAAP permits capitalization of E&E expenditure if certain criteria are met.[26] This allows us to examine whether this flexibility in reporting intangible assets in Australia further assists analysts in evaluating prospective outcomes of E&E activities. For these reasons, the Australian context provides a powerful setting to examine associations between the intensity of E&E activities and analysts' private information development activities and forecast accuracy.

The study finds that the proportion of private information contained in analysts' forecasts increases with E&E expenditure, consistent with analysts increasing their efforts to develop private information in response to the greater intensity of E&E activities. The study also finds that the accuracy of analysts' average forecasts increases with the intensity of E&E activities even after controlling for the number of forecasts and individual analyst forecast errors. This suggests that the improved accuracy in analysts' forecasts is at least partially associated with analysts' increased efforts in private information development. Overall, the results suggest that analysts develop more private information and use this to increase their forecast accuracy for firms with high exploration intensity.

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[25] The extractive industries are central to the ASX, with total market capitalization of $310 billion and over 1000 listed extractive companies, representing 28% of total market capitalization and 49% of all ASX listed companies by number (ASX, 2013a).

[26] Exploration and evaluation (E&E) expenditure is expenditure incurred by an entity in connection with the exploration for and evaluation of mineral resources before the technical feasibility and commercial viability of extracting a mineral resource are demonstrable (IASB, 2004).

The study investigates two factors that are associated with analysts' reliance on private information and their forecasting ability when facing the greater intensity in E&E activities. The study finds that capitalization of certain E&E expenditure enables managers to better communicate information about the probable future benefits of these exploration projects, which assists analysts' development of more useful private information and improves the accuracy of their forecasts. The study also finds that the effect of exploration intensity on the analysts' information environment is more pronounced for firms facing the greatest information asymmetry: those with substantial E&E activities but limited or no production activities.

This study contributes to the literature in three ways. First, the study adds to the literature studying information asymmetry in the extractive industries. Notwithstanding the major global importance of the extractive industries, there are a surprisingly small number of studies on the extractive industries in a capital markets context. The study provides evidence of positive associations between the intensity of E&E activities, analysts' private information development activities and forecast performance. While prior research on the extractive industries recognizes the high information asymmetry associated with E&E activities (Ferguson and Crockett, 2003; Poskitt, 2005), the evidence suggests that analysts are able to reduce the high information asymmetry associated with E&E activities, by developing more private information and using it to improve their forecast accuracy. The findings of this study show that market participants can benefit from analysts' expertise in developing private information and can use analysts' forecasts to expand their information set when investing in extractive companies with high exploration intensity.

Second, the study provides further empirical evidence on the impact of intangible assets on analysts' forecast performance. The relevant question is whether the complex nature of intangible assets adversely affects analysts' forecast accuracy. Gu and Wang (2005) argue that due to differences in "diversity" and "innovation" between types of intangible assets, they may be associated with differential accuracy of analysts' forecasts. They show that analyst forecast accuracy is significantly lower for firms whose intangible assets are technology-based (R&D), and it is positively associated with intangible assets in the biotech, pharmaceutical, and medical equipment industries where highly stringent regulations make the process of innovation more standardised and changes in the value of intangibles more identifiable.

The results complement Gu and Wang (2005)'s findings, suggesting that, apart from intangibles-related regulations, the various degrees of "diversity" and "innovativeness" pertaining to the different types of intangible assets have an impact on their relation to analysts' forecast accuracy. In a scale-intensive industry like the extractive industry, there is limited scope for diversity through product differentiation, and the main driver for innovation is productivity improvement through increased process efficiency across E&E activities (Upstill and Hall, 2006). Although assessing the future prospects for exploration firms with substantial E&E activities can be complex, it follows a relatively standardised approach. Most decisions about exploration are based on geological statements, measurements and calculations and assessment of the underlying geological uncertainties (Kreuzer and Etheridge, 2010). With analysts' specialised (private) knowledge of disciplines such as geological sciences, they are able to identify the viability of commercial production from exploration developments based on the changing economics of extraction and processing. As claimed by the managing director and head of resources research in one prominent brokerage house, "You get a couple of good drill results and then a competent technical person who can look at the drill results, extrapolate them and say 'This has the potential to be a large resource.' And that's what you're looking for." (Baker, 2014, p.26). The findings support this notion that analysts are able to improve their forecast accuracy using their private information acquisition and processing skills for firms whose intangible assets with limited diversity and innovation.

Third, the findings shed some light on the effectiveness of accounting disclosure for E&E expenditure. The classification of E&E expenditure is a controversial topic that was recently reviewed by the International Accounting Standards Board (IASB, 2010).[27] Prior literature suggests that, compared with the full cost accounting method, an important advantage of other accounting methods such as the successful efforts and area of interest is that separating successful from unsuccessful investments may provide relevant information to investors (Naggar, 1978; Harris and Ohlson, 1987). The results provide some evidence of this advantage. The study finds that analysts' private information development activities are mainly related to capitalized E&E expenditure, suggesting that analysts may perceive expensed E&E costs from unsuccessful exploration projects to be irrelevant information.

The remainder of the paper is organized as follows. Section 2 provides background information and reviews the related literature. Section 3 develops the hypotheses. Section 4 describes the sample selection and defines the variables. Section 5 discusses the empirical analyses and the test results. Section 6 presents additional analyses. Section 7 concludes.

3.2 Background and Literature Review

3.2.1 Overview of the Extractive Industries and Accounting for E&E Expenditure

The extractive industries (comprising minerals and oil and gas) are defined as "those industries involved in finding and removing wasting natural resources located in or near the earth's crust" (IASC, 2000, p. 14). The processes of exploration and discovery of minerals, oil and natural gas deposits, development of those deposits, and extraction of the minerals, oil and natural gas, are referred to as extractive

[27] The IASB *Discussion Paper – Extractive Activities* was developed by a research team comprising members from the national accounting standard setters in Australia, Canada, Norway and South Africa. The *Discussion Paper* outlined a revised framework for accounting for extractive activities. After considering 141 comment letters received on the *Discussion Paper* in December 2012, the IASB decided to discontinue the project in favor of a broader intangible assets project which includes extractive activities as part of a broader consideration of intangible assets and research and development activities.

activities (IASB, 2010). Extractive activities begin with the exploration and evaluation of a geographical area of interest.[28] If the exploration and evaluation is successful, a mineral deposit can be developed and commercial production can commence.[29]

Uncertainties associated with extractive activities are significant (IASC, 2000). The exploration and evaluation phases of a project are arguably the most risky as it is common to have insufficient data to evaluate whether a deposit of minerals or oil and gas can generate revenue from its extraction and sale (IASB, 2010). In other words, during the exploration and evaluation phases of a project, extractive companies have yet to establish the commercial viability of the project or the availability of financing, or to identify the existence of markets or long-term contracts for the product.

Significant upfront investment, uncertainty over prospects and long project lives create specific challenges in accounting for costs incurred in the exploration and evaluation phases of a project.[30] The accounting treatment of E&E expenditure (capitalizing or expensing) can have a fundamental impact on the annual financial statements and reported financial results of an extractive company, particularly for a junior exploration company with no major producing assets. Currently under IFRS 6 *Exploration for and Evaluation of Mineral Resources*, which became effective in 2006 and specifically addresses extractive activities, extractive companies have accounted for E&E costs in a variety of ways, including the successful efforts, full

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[28] Exploration is the detailed examination of a geographical area of interest that has shown sufficient mineral-producing potential to merit further exploration. Exploration activities include: conducting topographical, geological, geochemical and geophysical studies; and carrying out exploratory drilling, trenching and sampling activities. Evaluation activities involve determining the technical feasibility and commercial viability of mineral deposits that have been found through exploration (IASB, 2010).

[29] Development is the establishment of access to the mineral reserve and other preparations for commercial production. Development activities often continue during production. Production involves the extraction of the natural resources from the earth and the related processes necessary to make the produced resource marketable or transportable (IASB, 2010).

[30] The costs of exploration are for discovering resources; the costs of evaluation are for proving the technical feasibility and commercial viability of any resources found. In comparison, the costs of development relate to gaining access to the resources after the decision has been made to develop the mine. The costs of production are the cost of producing the saleable product on a commercial scale and incudes all extraction and treatment costs (PricewaterhouseCoopers, 2007).

cost and area of interest accounting methods.[31] Both the successful efforts and full cost accounting methods are permitted for use mostly by oil and gas companies in the U.S., Canada and the U.K.. In Australia, extractive companies are required to adopt the area of interest accounting method.[32]

The accounting treatment of E&E expenditure in Australia, both before and after mandatory adoption of IFRS in 2005, permits a significant degree of management discretion over the criteria for E&E expenditure to be capitalized (Wu et al., 2010). The Australian standard, AASB 6 *Exploration for and Evaluation of Mineral Resources*, specifies that asset recognition of E&E expenditure be subject to criteria related to the expectation that E&E expenditure will be recouped.[33] As suggested by Wu et al. (2010), the standard is less restrictive in allowing the capitalization of E&E expenditure at the discretion of management before reaching the stage at which future economic benefits can be verified. This allows us to examine whether this flexibility in reporting intangible assets in Australia further assists analysts in developing private information on the future prospects of exploration firms.

3.2.2 E&E Expenditure and Capital Markets

The extractive industries in Australia make a significant economic contribution to the Australian economy.[34] The recently improved global commodities market has

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[31] IFRS 6 allows companies to carry over to IFRS their previous GAAP practice to a large extent.
[32] An area of interest refers to an individual geological area whereby the presence of a mineral deposit or an oil or natural gas field is considered favourable or has been proven to exist (AASB, 2004).
[33] Paragraphs 7.1 and 7.2 of AASB 6 require that for each area of interest, exploration and evaluation costs shall either be:
"(i) expensed as incurred; or
(ii) partially or fully capitalized, and recognized as an exploration and evaluation asset if the following conditions are satisfied.
(a) the rights to tenure of the area of interest are current, and
(b) at least one of the following two conditions is also met:
(i) the exploration and evaluation expenditures are expected to be recouped through successful development and exploitation, or by sale, and
(ii) exploration and evaluation activities in the area of interest have not at the reporting date reached a stage of reasonable assessment to determine the recoverable reserves, but active operations are continuing."
(Similar criteria appear in the pre IFRS equivalent AASB 1022 of Australian GAAP).
[34] It is the nation's largest single export sector. In 2012-13, mineral and energy exports accounted for an estimated 86% (A$ 175 billion) of Australian commodity exports, and 58% of total goods and services

stimulated extractive companies to increase exploration expenditure, resulting in the industry's aggregate exploration spending reaching $21.5 billion in 2012, the highest total on record. Australia accounted for over 12% of this record level of global exploration expenditure (SNL Metal Economics Group, 2013).

The ability of Australia's extractive industries to sustain their growth and expand their contribution to national economic performance is critically dependent on continued investment in resource exploration (ABARES, 2009). A significant majority of exploration projects is funded by equity. In particular, junior exploration companies rely on equity financing to fund exploration because most of them do not generate revenue from producing mines (SNL Metals Economics Group, 2013). During 2009 to 2013, there were over 400 new junior resource floats on the ASX (ASX, 2013b). The heavy reliance on equity investors to fund the capital intensive development of exploration projects makes it important for investors to understand the future implications of E&E expenditure. Investors also rely on analysts' information because of their prominent role in analyzing, interpreting, and disseminating information to capital market participants.

3.2.3 Capital Markets Literature on E&E Activities

Investing in extractive companies in Australia offers high reward investment opportunities. How (2000) reports that mining initial public offerings (IPOs) in Australia generated an average initial return of over 100% during the period from 1979 to 1990, and that their longer term performance is superior to non-mining companies. From a survey of 179 Australian junior exploration companies that floated during 2001 to 2006, Kreuzer et al. (2007) find that the 20 top-performing junior explorers gained an annual return of over 300% in 2006.

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exports (BREE, 2013). During that period, the mineral resources industries accounted for 8.6% (A$122 billion) of Australia's gross domestic product (ABS, 2013), and at 266,000 employees, more than 50% above the level of three years earlier (BREE, 2013).

Investors in extractive companies are nevertheless likely to face pronounced information asymmetry and have difficulty interpreting technical non-financial information disclosed by extractive companies. Poskitt (2005) observes that extractive companies "appear to be over-represented in practices that are consistent with the existence of strong and potentially valuable information asymmetries" (p. 202). He reports excessive informational disadvantages faced by investors in extractive companies: three of the four cases of market manipulation allegations and two of the four cases of insider trading allegations by the Australian Securities and Investments Commission (ASIC) between July 1997 and June 2002 were made against extractive companies.[35]

There is also consistent evidence on the difficulty of interpreting the price implications of complex non-financial information announced by extractive companies. Ferguson and Crockett (2003) find that a gold discovery by one exploration company impacted the market value of other exploration companies with nearby leases. The competing explorers that received the most press coverage initially recorded higher returns but subsequently significantly underperformed. A similar conclusion is reached by Bird et al. (2013): the use of positive adjectives in their exploration announcement headlines triggers a large positive share price response for these extractive companies. Taken together, investors facing high information asymmetry and complexity of non-financial information are likely to have high demand for analysts' information about extractive companies, particularly in relation to their E&E activities.

3.2.4 Analysts' Forecasts and Intangible Assets

Prior research suggests that analysts have incentives to search for private information in an environment in which information asymmetry is pronounced and investors can derive greater benefits from it (e.g., Barth et al., 2001; Barron et al., 2002; Frankel et

[35] Market manipulation allegations were made against Reef Mining NL, Diversified Mineral Resources NL and Diamond Rose NL. Insider trading allegations were made against Mt Kersey Mining NL and Carpenter Pacific Resources NL.

al., 2006). Barth et al. (2001) find that analysts expend more resources collecting and analyzing information for firms with high R&D intensity in response to higher investor demand for information about them. Barron et al. (2002) document that analysts supplement firms' financial information by placing relatively greater reliance on their private information when deriving earnings forecasts for firms with significant intangible assets.

While Barron et al. (1998) argue that analysts' private information development can improve the accuracy of the average forecast after idiosyncratic errors in the individual forecasts are averaged out, analysts' forecast performance may still deteriorate due to the complexity of information associated with intangible assets. Gu and Wang (2005) report a negative association between analyst forecast accuracy and the level of intangible assets that are above the industry average. Gu and Wang further suggest that the various degrees of "diversity" and "innovation" pertaining to the different types of intangible assets have an impact on their relation to analysts' forecasts. They provide evidence that analyst forecast accuracy improves with levels of intangible assets in the biotech, pharmaceutical and medical equipment industries where highly stringent regulations make the process of innovation more standardized and changes in the value of intangibles more identifiable. In this paper, I argue that different types of intangible assets may differ in degree of "diversity" and "innovativeness". Specifically, I examine whether analysts are able to improve their forecast performance using their private information development skills for intangible assets with limited diversity and innovation.

Although assessing the future prospects for exploration firms with substantial E&E activities can be complex, it follows a relatively more standardised approach than the technology-based intangibles (R&D) examined in Gu and Wang (2005). The scope for product differentiation is limited in the extractive industry and the main driver for innovation is productivity improvement through increased process efficiency across E&E activities (Upstill and Hall, 2006). Most decisions about exploration are based on geological statements, measurements and calculations and assessment of the underlying geological uncertainties (Kreuzer and Etheridge, 2010). In addition, compared with the lack of conventional tools to value technology-based intangible assets (Gu and Wang, 2005), a number of readily available common valuation methods are used in the extractive industry for valuing mineral exploration properties even at the early stage of exploration, for example, the geoscience factor method, the market approach method and the appraised value method.[36] This standardised approach may help analysts who have specialised knowledge of disciplines such as the geological sciences to better understand and interpret information on the future prospects of E&E activities.

3.3 Hypothesis Development

There are a number of reasons why it is expected that analysts' reliance on private information to increase with the intensity of E&E activities. First, substantial information asymmetry associated with E&E activities has long been recognized in the extractive industries, including difficulty interpreting complex non-financial information, nature of mining activities and absence of established earnings history specially for junior exploration companies. Ferguson et al. (2011) suggest that the successful evaluation of exploration and mining companies requires that investors go beyond the familiar territory of financial statements, and into the analysis of complex geological reports that cover such matters as metal purity levels, drilling intercepts and geochemical composition. Investors may find these reports difficult to interpret, leaving them incapable of effectively evaluating these firms. Ferguson and Crockett (2003) and Bird et al. (2013) conclude that investors who have little geological

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[36] Using ranked and weighted geological aspects such as proximity to mines, deposits and the significance of the camp and the commodity sought, the Geoscience Factor Method is a subjective, matrix-based valuation methodology for mineral exploration properties that do not contain exploitable resources. The Market Approach Method is based on the value of recent (cash- or share-based) transactions that are similar in terms of scope, time, place and commodity. The Appraised Value Method is based on the premise that a mineral exploration property is worth meaningful past exploration expenditure (in dollars of the day) plus warranted future costs (i.e., expenditure base). Readers are referred to Kilburn (1990), Thompson (2000) and Lilford and Minnitt (2005) for a more detailed discussion of valuation methodologies on mineral properties.

expertise may rely more on media reports or exploration announcements with positive adjectives because of the complexity of geological information.

Moreover, greater information asymmetry is also involved in complex underground mines relative to open pit mines because mine failure may be more pervasive for underground mines (Ferguson et al., 2011). Mineral deposits typically come in two forms – open pit or underground. With open pit deposits, mine overburden is removed, exposing the ore body and allowing removal of ore grade material to the processing plant. Open pit mining is preferred when the ore body is situated in relatively close proximity to the surface. This feature minimises the extent of costly waste material to be removed, thus lowering expected cash costs. In contrast, underground operations are higher risk with deeper ore bodies and safety issues from possible rock falls or flooding.

Information asymmetry is arguably higher for junior exploration companies compared to established mining companies because of the absence of an established earnings history (Ferguson and Crockett, 2003). Junior exploration companies, who have no product sales and few assets but do have significant amounts of E&E expenditure, typically have highly uncertain earnings potential with little or no past or current earnings or positive cash flows to indicate their potential (Iddon et al., 2013). In other words, while junior exploration companies can potentially generate considerable future earnings, they are more likely to exhaust all their capital before making profits. For these exploration companies, the risks and uncertainties of their exploration projects are critical to their very existence, as the continuation of these companies as a going concern is closely tied to the successful delineation and extraction of economic deposits. Hence, reported earnings may be less useful for assessments of the future prospects of such firms with greater exploration intensity, causing analysts to seek and process private information, including non-financial information such as geological data.

Second, in the extractive industries, valuing the overall exploration and economic potential of the mineral assets requires analysts to take into account a wide range of input parameters such as geological setting, style of mineralization, grade-tonnage potential and regional endowment, commodity prices, metallurgy and mineability, infrastructure and access, and security of tenure and sovereign risk (Kreuzer and Etheridge, 2010). Most of these input parameters at the exploration and evaluation phases of an exploration project involve inherent uncertainty. For example, some input parameters depend on statistical inferences drawn from drilling, geochemical and geophysical data which may prove to be unreliable and are dependent on market prices, mining, processing and inventory costs. Other economic and technical parameters also vary from period to period and from operation to operation (Taylor et al., 2012). Over-estimation or under-estimation of the underlying geological uncertainties can augment of the overall risky nature of the asset (Bárdossy and Fodor, 2001).[37] These uncertainties engage analysts in a constant search for information to improve their foresight and decision making.

Taken together, the high information asymmetry and inherent uncertainty associated with E&E activities increase the likelihood of mispricing opportunities for firms with high levels of E&E expenditure, providing analysts with greater incentives to seek and evaluate private information to differentiate their expertise (Brown et al., 2014). Prior literature suggests that analysts have incentives to build their reputation through accurate forecasts and recommendations (Jackson, 2005; Simon and Curtis, 2011). With better reputations, analysts are more likely to be promoted and to receive higher compensation (Hong and Kubik, 2003; Groysberg et al., 2011). Therefore, it is expected that analysts' earnings forecasts for firms with more intensive E&E

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[37] It is possible that the uncertainty about commodity price might affect the level of E&E activities, but its impact is not likely to vary cross-sectionally as it applies to the industry as a whole. Furthermore, Brown and Burdekin (2000) argue that the share prices of exploration companies are more sensitive to changes in the probability of discovering an economic deposit than to the commodity price. There is no shortage of anecdotal evidence to support this proposition. For example, in November 2001 the stock price of Minotaur Resources jumped from A17c to A$1.65 in a single day on announcement of early drilling results and subsequent market speculation that it had discovered a rich copper deposit in South Australia (Poskitt, 2005).

activities contain a greater proportion of private information. The first hypothesis, stated in the alternate form, is:

H1: *The proportion of private information contained in analysts' forecasts is positively associated with the intensity of E&E activities.*

Increases in analysts' private information development activities enhance the overall information environment (Lang et al., 2003). At the same time, individual forecasts become more idiosyncratic when analysts place greater reliance on their private information because their expertise in gathering and processing private information varies across individual analysts. The accuracy of the average forecast is, however, improved because relatively more analysts' idiosyncratic forecast errors are diversified away through the aggregation process (Barron et al., 1998). Furthermore, Barron et al. (2008) empirically demonstrate that the accuracy of analysts' mean forecasts increases with the proportion of private information contained in their forecasts. Where analysts' private information plays a vital role in evaluating prospective outcomes of E&E activities, the accuracy of analysts' average forecasts is expected to increase with the intensity of E&E activities if analysts undertake relatively more private information development activities and their forecasts contain greater amounts of private information.

On the other hand, there could be a negative association between exploration intensity and the accuracy of analysts' average forecasts. Investing in intangible assets, including exploration projects, involves substantial uncertainty about prospective outcomes, which complicates the analyst's task of arriving at reliable earnings estimates and increases information processing costs (Gu and Wang, 2005). High information processing costs can adversely affect analysts' forecasts (Frankel et al., 2006). In particular, the greater information asymmetry and complexity of non-financial information typically involved in exploration projects can impede analysts' ability to provide accurate forecasts.

While the latter argument is acknowledged, the nature of E&E activities favours the first argument. The second hypothesis, stated in the alternate form, is:

H2: *The accuracy of analysts' average forecasts is positively associated with the intensity of E&E activities.*

3.4 Sample Selection and Variable Definitions

3.4.1 Sample Selection

The empirical tests employ data from four sources. Financial statement data are obtained from the Morningstar DataLink database. Analyst forecast data are obtained from the I/B/E/S International Summary File. Share prices and market capitalization information are sourced from the CRIF Share Price and Price Relative (SPPR) database. As noted in section 3.4.2, I manually collect annual E&E expenditure data from the financial statements of ASX-listed extractive companies through the Morningstar DatAnalysis database.

Of more than 3,000 firm-years reporting E&E expenditure in annual reports or for which E&E expenditure can be estimated using other financial statement line items for the period between the fiscal years 1993 and 2009, 817 firm-years have analyst forecast data available in the I/B/E/S database. The substantial reduction in sample size is consistent with the fact that many listed junior exploration companies with no product sales are unlikely to attract analyst following. To control for potential outliers, price-deflated forecast errors greater than 100% are excluded, which reduces the sample by 36 observations (Richardson et al., 2004). The final sample consists of 781 firm-year observations, representing 166 unique firms. Because I need to calculate forecast dispersion, which requires a minimum of two analysts' forecasts in each firm-year to construct measures from the Barron et al. (1998) model, the sample for *CONSENSUS*, *COMMON* and *PRIVATE* is reduced to 620 firm-years.

3.4.2 Proxy for the Intensity of E&E activities

Similar to the measures of R&D intensity of Aboody and Lev (1998) and Oswald and Zarowin (2007), I use the annual E&E expenditure (capitalized E&E expenditure plus E&E expense) scaled by total assets as a proxy for the intensity of E&E activities. Reported financial numbers for firms that capitalize E&E expenditure are re-stated to be on an "as-if-expensing" basis, so earnings and other related accounting numbers between firms that capitalize E&E expenditure and firms that expense their E&E outlays when incurred are comparable (Oswald and Zarowin, 2007).[38] High levels of scaled E&E expenditure indicate a greater intensity of E&E activities.

Reviewing the ASX-listed extractive companies' financial statements from the ASPECT Annual Reports Online website, I manually collect E&E expense and capitalized E&E expenditure data from both the income statement and the statement of financial position. If a firm capitalizes E&E expenditure, it reports capitalized E&E expenditure in the notes to the statement of financial position. If a firm does not report capitalized E&E expenditure directly, I estimate it using other financial statement line items.[39]

3.4.3 Measuring Analysts' Forecast Accuracy

Analysts' absolute forecast error (*AFE*) is used to measure analysts' forecast accuracy. I first calculate *AFE* for firm *i* in fiscal year *t* as follows:

$$AFE_{i,t} = |\text{Actual EPS}_{i,t} - \text{Average EPS Forecast}_{i,t}| \,/\, \text{Price}_{i,\,t\text{-}1}$$

[38] For firms that capitalize E&E expenditure, their total assets on an "as-if-expensing" basis are estimated by subtracting the amount of E&E assets from reported total assets.

[39] For example, capitalized E&E expenditure is estimated by subtracting the amount of impairment loss for E&E assets, the amount of E&E assets written off, the amount of E&E assets disposed of, the amount of E&E assets transferred to other accounts, and also subtracting the opening balance of E&E assets from the closing balance of E&E assets. If the value of estimated capitalized E&E expenditure is negative, the firm-year observation is excluded. There are 42 firm-year observations with negative value of estimated capitalized E&E expenditure.

where Actual $\text{EPS}_{i,t}$ is the actual I/B/E/S annual earnings per share for firm *i* in year *t*, Average EPS $\text{Forecast}_{i,t}$ is the I/B/E/S one-year ahead mean consensus forecast for firm *i* and year *t*, $\text{Price}_{i,\ t\text{-}1}$ is share price of firm *i* at the end of year *t*-1.[40] I then compute the average *AFE* as the simple average of the measure across months 1 to 12 following the firm's prior fiscal year-end (Lang and Lundholm, 1996).

3.4.4 Measuring Analysts' Private Information

In predicting future earnings, each analyst possesses both common information shared by all analysts and private information available only to himself or herself. Barron et al. (1998) suggest that the analyst's forecast error comprises a common forecast error due to imprecise public information and an idiosyncratic forecast error due to imprecise private information. The common component of error in analyst forecasts arises from the impact of unanticipated aggregate shocks that affect earnings. It relates to the uncertainty in information that is common to all analysts. The idiosyncratic component of error in analyst forecasts due to imprecise private information is individual-specific, arising from analysts' different information processing skills and forecast modelling techniques.

I use the analyst consensus construct (*CONSENSUS*) and its common (*COMMON*) and private information components (*PRIVATE*) developed by Barron et al. (1998) to measure the average proportion of private information conveyed in analysts' forecasts. In their model, the precision of common information (*h*) and the precision of private information (*s*) are estimated using observable properties of analysts' forecasts as follows (Barron et al., 1998; Proposition 1, p. 427):

$$h = \frac{(SE - \frac{D}{N})}{[\left(1 - \frac{1}{N}\right) D + SE]^2}, \quad s = \frac{D}{[\left(1 - \frac{1}{N}\right) D + SE]^2}, \quad CONSENSUS = \frac{h}{h + s}$$

[40] The results are similar using the median forecast rather than the mean forecast.

where *N* is the number of analysts' forecasts. *D* is the sample variance of analysts' individual forecasts; and *SE* is the squared error in the mean forecast, calculated as the squared difference between the mean forecast and actual earnings, that is, (*Actual EPS – Mean EPS Forecast*)^2.

Because the estimated values of *h* and *s* are highly skewed, I use their square roots as the common information (*COMMON*) and private information component (*PRIVATE*) variables following Begley et al. (2009):[41]

$COMMON = \sqrt{h}$, $\quad\quad PRIVATE = \sqrt{s}$

3.4.5 Control Variables

To control for other firm-specific factors that might affect the information environment of analysts, a set of control variables is included in the analyses: firm size, change in earnings, losses, leverage, analyst coverage and market-to-book ratio. The general information environment is likely to be richer for larger companies, suggesting that firm size may have a decreasing effect on analysts' forecast errors and be positively associated with the quantity of information available to investors (Lim, 2001). Thus, I control for firm size (*SIZE*) in the analyses, using the logarithm of market value of equity. The change in earnings has been shown, in prior research, to affect analysts' forecasts and incentives to develop private information. Lang and Lundholm (1996) find that analysts' forecasts are less accurate when there is a large change in earnings. Stickel (1989) and Barron et al. (2002) suggest that greater earnings surprises may encourage analysts to increase their private information development in order to maintain the precision of their forecasts. A control for earnings change (*EARNCHANGE*) is therefore included in the regressions, using the absolute value of the difference between the current year's actual earnings per share and last year's actual earnings per share divided by the share price at the end of last year.

[41] Using *h* and *s* as measures of *COMMON* and *PRIVATE* without taking square roots obtains similar results.

Hwang et al. (1996) find that analyst forecasts of losses are, on average, less accurate than forecasts of profits, indicating analysts find it difficult to forecast earnings for firms that report losses. To control for the effect of losses, an indicator variable (*LOSS*) is included, coded one for loss firm-years and zero otherwise. Hope (2003) documents that firms that are highly leveraged tend to have more variation in earnings and greater analyst forecast errors. Thus, the leverage proxy (*LEVERAGE*), measured as total liabilities divided by the book value of equity, is included in the regressions. Following Lys and Soo (1995), I include a control variable for analyst coverage (*COVER*). Lys and Soo find that the forecast accuracy is improved with a larger analyst following as the competition among analysts is increased. Therefore, inclusion of a measure of analyst coverage as an independent variable should control for such factors. To control for the effect of growth opportunities, the market-to-book ratio (*MB*) is included in the analyses.[42] Prior research finds that growth firms tend to attract a larger analyst following, indicating greater investor demand for private information about these firms (Bhushan, 1989; O'Brien and Bhushan, 1990; Barth et al., 2001).

3.5 Empirical Analyses

3.5.1 Estimated Equations

The study conducts the main analysis in two steps. First, the study examines whether analysts' private information acquisition increases with the intensity of E&E activities. Next, the study investigates whether the intensity of E&E activities is associated with analysts' forecast accuracy, using ordinary least-squares regressions. The general form of the regression models is presented as follows (all variables are calculated each year for each firm, and the firm subscript is suppressed):

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[42] The market-to-book ratio measures not only growth opportunities but also intangible assets. The inclusion of this control variable potentially reduces the power of the tests.

$$Forecast\ Property_t = \beta_0 + \beta_1 EXPL_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 EARNCHANGE_{t-1} + \beta_4 LOSS_t + \beta_5 LEVERAGE_{t-1} + \beta_6 COVER_t + \beta_7 MB_{t-1} + \varepsilon_t \quad (1)$$

where the subscript *t* refers to year *t*; Forecast Property refers to *CONSENSUS, PRIVATE* and *AFE*; *CONSENSUS* is the ratio of analysts' common information to their total information, calculated using the Barron et al. (1998) model (Proposition 1, p. 427); *PRIVATE* is the private information component in analysts' consensus, calculated using the Barron et al. (1998) model (Corollary 1, p. 428) and taking the square root; *AFE* is the absolute forecast error for year *t*, measured as the absolute value of the difference between the firm's actual and forecasted annual earnings per share for year *t*, divided by share price at the end of year *t*-1; *EXPL* is the annual E&E expenditure (capitalized E&E expenditure plus E&E expense) for year *t*-1 divided by total assets at the end of year *t*-1;[43] *SIZE* is logarithm of market value of equity at the end of year *t*-1; *EARNCHANGE* is the absolute value of the difference between current year's actual earnings per share and last year's actual earnings per share, scaled by share price at the end of year *t*-1;[44] *LOSS* is an indicator variable that equals one if the firm reports a loss for year *t* and zero otherwise. *LEVERAGE* is total liabilities divided by book value of equity at the end of year *t*-1;[45] *COVER* is the number of analysts providing earnings forecasts for the firm for year *t*; and *MB* is the market-to-book ratio at the end of year *t*-1.

H1 predicts that the association between the intensity of E&E activities and the proportion of private information contained in analysts' forecasts is positive. If the relation between *CONSENSUS* and *EXPL* is estimated to be negative, and the relation between *PRIVATE* and *EXPL* is estimated to be positive, H1 is supported. H2 predicts that *AFE* is positively associated with *EXPL*. An estimated positive coefficient on *EXPL* supports H2.

[43] Total assets are re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure.
[44] Actual earnings per share is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure.
[45] Book value of equity is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure.

3.5.2 Descriptive Statistics

Table 3.1 presents descriptive statistics relating to the distribution of regression variables. All variables are winsorized at the 1% and 99% levels. The mean (median) of *CONSENSUS* is 0.6 (0.63), indicating that analysts rely more on common information than private information in forming their forecasts. There is a significant variation in the distribution of *CONSENSUS* with a standard deviation of 0.273, which is similar to prior research (e.g., Barron et al., 2002).[46] The sample firms have a mean (median) forecast error of 7.4% (2.2%) of share price, which is much greater than those reported in prior studies (e.g., Chen, 2010).[47] The large forecast errors reflect the difficulty in forecasting future earnings for exploration intensive companies. The mean (median) of *EXPL* is 0.073 (0.032), with a standard deviation of 0.104, indicating that on average (at the median) the extractive companies with analyst coverage invest 7.3% (3.2%) of total assets in E&E activities with a high variation across the sample firms. The mean value is more than twice the size of the median value, consistent with the concentration of intensive E&E activities in certain firms.

<Insert Table 3.1 about Here>

The sample firms are covered by 6 (4) analysts on average (at the median). The median firm has a log market value of equity of $8.506, equivalent to market value of $321 million, and makes profits with earnings growth of 3.1%. It is consistent with large and profitable firms attracting analyst following. Also, the median firm has a debt to equity ratio of 65.7% and a market to book ratio of 1.98.

Table 3.2 presents the Pearson correlations among the variables. It shows a significantly positive correlation between *PRIVATE* and *EXPL*. Furthermore, *EXPL* is negatively related to *SIZE*, *LEVERAGE* and *COVER*, consistent with junior exploration companies with little debt financing and low analyst following playing a

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[46] Barron et al. (2002) reports that the mean (median) and standard deviation of *CONSENSUS* for the U.S. firms with intangible assets are 0.752 (0.7877) and 0.2465 respectively (p. 303).

[47] In Chen (2010)'s sample of Australian companies with analysts following during 1987–2007, analysts' mean (median) forecast error is 0.927% (0.885%) of share price.

critical role in investing in exploration projects to find new assets (PricewaterhouseCoopers, 2013). Also, *EXPL* is positively associated with *LOSS* and *MB*, indicating that greater E&E intensity represents growth opportunities but high potential of making losses. By construction, *CONSENSUS* is strongly related to *PRIVATE* and *AFE*.

<Insert Table 3.2 about Here>

3.5.3 Regression Results

Columns (1), (2) and (3) of Table 3.3 report the results of estimating equation (1), where properties of analysts' information environment (measured by *CONSENSUS*, *PRIVATE*, or *AFE*) are regressed on the exploration intensity and control variables.[48] Consistent with the prediction, the estimated coefficient on *EXPL* for the *CONSENSUS* regression in Column (1) is significantly negative at less than 10% level (Coeff. = -0.233, *t*-stat. = -1.7). Furthermore, the estimated coefficient on *EXPL* is positive and statistically significant for the *PRIVATE* regression in Column (2) (Coeff. = 128.798, *t*-stat. = 4.21). The results indicate that the degree of consensus among analysts is lower for firms with higher levels of E&E expenditure and the proportion of private information contained in analysts' forecasts increases with the intensity of E&E activities. The results support H1 and suggest that, in response to the greater intensity of E&E activities, analysts not only increase their reliance on the amount of private information relative to the amount of common information shared by all analysts, but also acquire and process more private information to meet investor demand.

<Insert Table 3.3 about Here>

Column (3) of Table 3.3 presents evidence on H2 from the regression of analysts' forecast errors on the exploration intensity and control variables. The estimated

[48] I report results of all estimations after winsorizing the continuous variables at the 1% and 99% levels. Clustering at the firm and year level or the firm level leads to the similar inference. The results are similar using the sample of 620 firm-year observations rather than the sample of 781 firm-year observations for all *AFE* regressions in the main and additional analyses.

coefficient on *EXPL* is significantly negative at -0.151 (*t*-stat. = -3.36). The results support H2 and suggest that the accuracy of analysts' average forecasts improves with the intensity of E&E activities.[49] The explanatory power of the regression is substantial with an adjusted R^2 of 45.7%.

The estimated effect of increasing intensity of E&E activities on analysts' forecast accuracy appears to be economically significant. A one-standard-deviation increase in the exploration intensity is associated with 21% reduction in analysts' forecast errors.[50] The results are consistent with analysts improving their forecast performance by expending more resources and efforts in private information development activities in response to the increasing intensity of E&E activities. The findings complement prior evidence on the differential accuracy in analysts' forecasts for firms with different types of intangible assets (Gu and Wang, 2005). It is possible that the limited scope of product differentiation in the extractive industries, a relatively standard and transparent approach of assessing future prospects of firms with various stages of E&E activities and analysts' technical skills in geological sciences help analysts enhance their forecast performance.

As for the control variables, the coefficient on *SIZE* is significantly positive in the *CONSENSUS* regression and significantly negative in the *PRIVATE* and *AFE* regressions as expected, indicating that the quantity of information available to investors is positively associated with firm size and analysts are more accurate for larger firms with richer information environments. Consistent with prior research (Lang and Lundholm, 1996), the coefficient on *EARNCHANGE* is significantly positive in the *AFE* regression, suggesting that analyst forecasts are less accurate when there is a larger earnings change. Significantly positive coefficients on *LOSS* in both *CONSENSUS* and *AFE* regressions suggest that analysts are likely to adopt a simple forecasting process (e.g., a simple random walk forecast) if earnings are more

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[49] Using the annual E&E expenditure scaled by market value of equity rather than total assets at the end of year *t*-1, yields consistent results for all *AFE* regressions in the main and additional analyses.
[50] 21% = -0.151×0.104/0.074

difficult to forecast (Barron et al., 2002). While this increases errors in analysts' forecasts, it will also increase correlation in these forecast errors (*CONSENSUS*). The coefficient on *MB* is significantly negative in the *CONSENSUS* regression and positive in the *PRIVATE* regression, consistent with greater investor demand for private information on firms with high growth opportunities (Bhushan, 1989; O'Brien and Bhushan, 1990; Barth et al., 2001).

3.5.4 Controlling for Individual Analysts' Forecast Errors

Barron et al. (2008) argue that an increase in the accuracy of analysts' average forecasts is attributable to three factors: (1) an increase in the number of analysts' forecasts; (2) a decrease in individual analysts' forecast errors; and (3) an increase in analysts' reliance on private information. The primary argument for H2 is the third factor. To examine the robustness of the results to the other two factors associated with analysts' average forecast accuracy, I re-run the analyses, controlling for: (1) the number of forecasts; and (2) individual analysts' forecast errors. I modify equation (1) by including an additional variable: the average squared error in individual forecasts (*INDERROR*), measured using the Barron et al. (1998) model (Proposition 1, p. 427).[51]

The results are presented in Column (4) of Table 3.3. I use the sample with 620 firm-years because a minimum of two analysts' forecasts in each firm-year is required to construct the measure of *INDERROR*. The estimated coefficient on *EXPL* is significantly negative after controlling for *COVER* and *INDERROR* (Coeff. = -0.076, *t*-stat. = -1.97), and it is less negative than that reported in Column (3) of Table 3.3, suggesting that *INDERROR* (Coeff. = 0.026, *t*-stat. = 5.96) also contributes to the association between *EXPL* and *AFE*. Moreover, including *INDERROR* in equation (1) improves the explanatory power of the regression with an adjusted R^2 of 61.4%.

[51] $INDERROR = \left(1 - \frac{1}{N}\right) D + SE$, where *N* is the number of analysts' forecasts; *D* is the sample variance of the analysts' individual forecasts; and *SE* is the squared error in the mean forecast, calculated as the squared difference between the mean forecast and actual earnings, that is, (*Actual EPS – Mean EPS Forecast*)^2 (Barron et al., 1998).

In summary, the results are consistent with the notion that individual analysts incorporate more private information into their forecasts for firms with greater exploration intensity, which improves the accuracy of analysts' average forecasts.

3.5.5 Robustness to Predictability of Earnings

The improved forecast accuracy for firms with greater exploration intensity may be driven by higher earnings predictability of these firms. To examine how the predictability of earnings relates to the levels of E&E expenditure, I regress actual *EPS* for year *t* on actual *EPS* for year *t*-1 and investigate whether the estimated coefficient on Actual EPS_{t-1} varies by tercile of E&E expenditure as follows.[52]

$$Actual\ EPS_t = \beta_0 + \beta_1 Actual\ EPS_{t-1} + \varepsilon_t \tag{2}$$

The results are reported in Table 3.4. I find that the predictability of earnings significantly differs across groups with low, medium and high levels of E&E expenditure (F value = 30.41). The estimated persistence coefficient on Actual EPS_{t-1} is significantly lower for firms with high levels of E&E expenditure at 0.132 (*t*-stat. = 9.53), indicating a very low predictability of current earnings for future earnings at 13.2%. The low persistence of earnings for firms with the greater intensity of E&E activities suggests that it is difficult for analysts to assess the future prospects of these firms using publicly available accounting information. It provides support to the findings that analysts incorporate more private information into their forecasts for firms with greater exploration intensity.[53]

<Insert Table 3.4 about Here>

[52] The sample for the predictability of earnings is slightly smaller than the sample for *AFE* and consists of 762 firm-years because prior year's actual earnings are not available in I/B/E/S for some firm-years.

[53] It is also interesting to observe that the earnings persistence coefficient for firms with middle levels of E&E expenditure is the highest among the low, middle and high E&E expenditure groups. If I assume these firms with middle levels of E&E expenditure are industry norm, the results are consistent with the firm's intangible intensity deviated from the industry norm complicating analysts' forecasting task (Gu and Wang, 2005).

3.6 Additional Analyses

In this section, the study investigates factors associated with analysts' private information development on E&E activities. The study first examines whether capitalization of E&E expenditure has an impact on analysts' private information search activities and their forecast accuracy. Next, the study examine whether analysts respond differently if firms have different levels of production and E&E activities.

3.6.1 Accounting Treatment of E&E Expenditure

The accounting treatment of E&E expenditure (capitalizing or expensing) may impact analysts' forecasts. Capitalization, by providing information about the percentage of outlays capitalized and the period of amortization, may convey information to the market about the future economic outcomes of exploration projects, thus helping investors to discriminate between successful and unsuccessful projects. For example, Aboody and Lev (1998) find that capitalized software development costs improve the prediction of future earnings, suggesting that despite the subjectivity of management discretion inherent in capitalization, capitalization provides relevant information for investors. On the other hand, capitalization might not communicate value relevant information either because of deliberate biases introduced by managers, i.e., capitalization creates opportunities for managers to manipulate earnings by accelerating or delaying amortization of capitalized expenditure on projects with a low probability of success (Cazavan-Jeny et al., 2011); or because of the considerable uncertainty inherent in projections of future economic benefits of exploration projects.

In the face of high information asymmetry between managers and investors in the extractive industries, the study examines the decision to capitalise E&E expenditure, using the area of interest accounting method. Does this choice of accounting treatment by managers convey information to investors about the firm's future performance to make earnings more predictable?

The sample of 781 firm-years is divided into Capitalizers and Expensers, with a firm-year observation being defined as a Capitalizer if in that year the firm reports capitalized E&E expenditure; and otherwise being classified as an Expenser. This classification results in 689 firm-year Capitalizer observations (157 firms), and 92 firm-year Expenser observations (25 firms).[54] *EXPL* is split into three components: E&E expenditure expensed by Expensers (*EXPLEXPEXP*), E&E expenditure capitalized by Capitalizers (*EXPLCAP*) and E&E expenditure expensed by Capitalizers (*EXPLEXPCAP*). The high proportion of Capitalizers demonstrates that Australian GAAP is less restrictive in allowing the capitalization of E&E expenditure before it reaches the stage at which it generates future economic benefits (Wu et al., 2010). The descriptive statistics on firm characteristics of Capitalizers and Expensers (untabulated) indicates that Capitalizers have a significantly greater E&E intensity, larger earnings variability, a higher market to book ratio, and are followed by more analysts. However, the two groups are only marginally different in term of market capitalization.

I first estimate equation (3) using *CONSENSUS*, *COMMON* and *PRIVATE* as alternative dependent variables to examine the impact of capitalization of E&E expenditure on analysts' consensus, common and private information. Next I estimate equation (3) using *AFE* as a dependent variable to examine whether capitalization of E&E expenditure can reduce the uncertainty analysts have about the future economic outcomes of exploration projects, and thus improve the accuracy of their forecasts:

$$Forecast\ Property_t = \beta_0 + \beta_1 EXPLCAP_{t-1} + \beta_2 EXPLEXPCAP_{t-1}$$
$$+\beta_3 EXPLEXPEXP_{t-1} + \beta_4 SIZE_{t-1} + \beta_5 EARNCHANGE_{t-1}$$

---

[54] The number of Capitalizer and Expenser firms in total (182) exceeds the number of firms in the final sample (166) since a firm may be classified as both an Expenser and a Capitalizer during the sample period if the firm changed their E&E asset recognition policy. The results are similar if these firms are removed from the sample.

$$+\beta_6 LOSS_t + \beta_7 LEVERAGE_{t-1} + \beta_8 COVER_t + \beta_9 MB_{t-1}$$

$$+\varepsilon_t \qquad (3)$$

where the subscript *t* refers to year *t*; Forecast Property refers to *CONSENSUS*, *COMMON*, *PRIVATE* and *AFE*; *COMMON* is the common information component in analysts' consensus, calculated using the Barron et al. (1998) model (Corollary 1, p. 428) and taking the square root; *EXPLCAP* is the annual E&E expenditure capitalized by Capitalizers for year *t*-1 divided by total assets at the end of year *t*-1;[55] *EXPLEXPCAP* is the annual E&E expenditure expensed by Capitalizers for year *t*-1 divided by total assets at the end of year *t*-1; *EXPLEXPEXP* is the annual E&E expenditure expensed by Expensers for year *t*-1 divided by total assets at the end of year *t*-1; and all other variables are defined as in Table 3.1.

If managers convey value relevant information through their decision to capitalize or expense E&E expenditure, common information shared by all analysts is likely to expand and the coefficient on *EXPLCAP* is estimated to be positive in the *COMMON* regression. If analysts develop more private knowledge to complement the information conveyed by capitalizing E&E expenditure, the coefficient on *EXPLCAP* is estimated to be positive in the *PRIVATE* regression.

Table 3.5 reports the results of estimating equation (3).[56] In both the *COMMON* and *PRIVATE* regressions in columns (2) and (3), the estimated coefficients on *EXPLCAP* are positive and statistically significant (Coeff. = 49.801, *t*-stat. = 3.48; Coeff. = 127.099, *t*-stat. = 3.96), indicating that analysts' common and private information increases with capitalization of E&E expenditure. The results suggest that capitalization of E&E expenditure enables managers to better communicate information about the probable future benefits of exploration projects, and this is used by analysts to develop more private information. The coefficient on *EXPLCAP*

[55] Total assets is re-stated on an "as-if-expensing" basis for Capitalizers.

[56] Scaling capitalized and expensed E&E expenditure by market value of equity rather than total assets yields similar results.

is not statistically significant for the *CONSENSUS* regression in Column (1), suggesting that analysts' common and private information increase by similar degrees through managers' decision to capitalize E&E expenditure.

<Insert Table 3.5 about Here>

Column (4) of Table 3.5 reports the results of the *AFE* regression. The estimated coefficient on *EXPLCAP* is significantly negative (Coeff. = -0.171, *t*-stat. = -3.68). This result indicates that capitalization, by providing information about the percentage of outlays capitalized vs. expensed and about the period of amortization, enables management to communicate information about the success of exploration projects and their probable future benefits, helping analysts to discriminate between successful and unsuccessful exploration projects. The capitalized E&E outlays are informative for analysts to provide accurate forecasts. On the other hand, one could argue that systematically amortized capitalization outlays reduce the variability of E&E expense and hence make it easier for analysts to forecasts. This result should be interpreted with caution.

With respect to other variables, a significant positive coefficient on *EXPLEXPCAP* (Coeff. = 1.83, *t*-stat. = 2.98) suggests that expensed E&E outlays by Capitalizers do not provide useful information for analysts to improve their forecasts.[57] A marginally significant negative coefficient on *EXPLEXPEXP* (Coeff. = -0.751, *t*-stat. = 1.88) suggests that analyst forecast accuracy also increases with expensed E&E outlays by Expensers. In summary, the relations between the intensity of E&E activities and analysts' forecast property are mostly attributable to the capitalized E&E outlays. It suggests that the accounting policies that require managers to distinguish successful from unsuccessful investments may assist analysts in analyzing and interpreting relevant information.

[57] A significantly positive coefficient on *EXPLEXPCAP* is perhaps surprising. It indicates that analysts' forecast errors are positively associated with the level of E&E expenditure expensed by Capitalizers. If expensing of E&E expenditure by Capitalizers represents write-offs of unsuccessful exploration projects, this could make the firm's future prospects more uncertain and further complicates analysts' forecasting task. When the sample of 620 firm-years is used, the coefficient on *EXPLEXPCAP* becomes insignificant but the coefficients on *EXPLCAP* and *EXPLEXPEXP* are still significantly negative (untabulated).

3.6.2 *Producers vs. Non-producers*

The effect of increasing intensity of E&E activities on analysts' forecasts may vary between firms that engage primarily in E&E activities and those with substantial production activities. If analysts respond to the greater intensity of E&E activities by expending more resources and efforts on private information development, I expect that the effect of exploration intensity on analysts' forecasts is more pronounced for firms that heavily engage in E&E activities. For these firms, their future prospects largely depend on the economic outcomes of exploration projects. Analysts are more likely to increase their investments in private information development and analysis for such firms.

I partition sample firms into four groups based on the median values of their annual operating revenue *REV* ($112.583 million) and *EXPL* measure (0.032), where High is above or equal to the median and Low is below the median:

(1) Low *REV* and High *EXPL* group (*LRev_HExpl*)	(2) High *REV* and High *EXPL* group (*HRev_HExpl*)
(3) Low *REV* and Low *EXPL* group (*LRev_LExpl*)	(4) High *REV* and Low *EXPL* group (*HRev_LExpl*)

There are 256 firm-year observations in each of the *LRev_HExpl* and *HRev_LExpl* groups. The *HRev_HExpl* and *LRev_LExpl* groups have 135 and 134 firm-year observations respectively. The descriptive statistics on firm characteristics of these four groups (untabulated) reveals that firms in the *HRev_LExpl* group are significantly larger than those in the other three groups, invest less in exploration projects (1.1% of total assets on average) and are followed by more analysts (10 analysts at the median). The *HRev_LExpl* group are Producers and are largely production companies. Firms included in the *LRev_HExpl* group are smaller, spend heavily on exploration (16.5% of total assets on average), and have lower analyst coverage (two analysts at the median). The *LRev_HExpl* group are Non-producers and are firms that engage primarily in E&E activities. I compare the effect of exploration intensity on the analysts' information environment and their forecasting ability for each of the four groups using the following equation:

$$\begin{aligned} Forecast\ Property_t &= \beta_0 + \beta_1 EXPL_{t-1} \times LRev\_HExpl_{t-1} + \beta_2 EXPL_{t-1} \times HRev\_HExpl_{t-1} \\ &+ \beta_3 EXPL_{t-1} \times LRev\_LExpl_{t-1} + \beta_4 EXPL_{t-1} \times HRev\_LExpl_{t-1} \\ &+ \beta_5 SIZE_{t-1} + \beta_6 EARNCHANGE_{t-1} + \beta_7 LOSS_t + \beta_8 COVER_{t-1} \\ &+ \beta_9 LEVERAGE_{t-1} + \beta_{10} MB_{t-1} + \varepsilon_t \end{aligned} \quad (4)$$

where the subscript *t* refers to year *t*; Forecast Property refers to *CONSENSUS*, *COMMON*, *PRIVATE* and *AFE*; *LRev_HExpl* is an indicator variable that equals one if a firm-year observation is from the *LRev_HExpl* group; *HRev_HExpl*, *LRev_LExpl* and *HRev_LExpl* are indicator variables indicating firm-year observations from the *HRev_HExpl*, *LRev_LExpl* and *HRev_LExpl* groups; and the control variables are the same as in equation (1).

If the effect of increasing exploration intensity on analysts' forecasts is greater for firms with substantial E&E activities (Non-producers), I expect the coefficient on the interaction term *EXPL×LRev_HExpl* to be positive in the *PRIVATE* regression to reflect analysts' efforts in searching for more private information, and the coefficient on *EXPL×LRev_HExpl* to be negative in the *AFE* regression to reflect the greater accuracy of analysts' forecasts because of the improved information environment.

Panel A of Table 3.6 reports the results of estimating equation (4). The coefficient of interest is on *EXPL×LRev_HExpl*, which captures the effect of exploration intensity on the analysts' information environment for non-producers. In both the *COMMON* and *PRIVATE* regressions in Columns (2) and (3), the estimated coefficients on *EXPL×LRev_HExpl* are positive and statistically significant (Coeff. = 63.954, *t*-stat. = 4.23; Coeff. = 172.297, *t*-stat. = 5.07), indicating that analysts' common and private information increases with the intensity of E&E activities for non-producers.

Because the future prospects of non-producers largely depend on the economic outcomes of their exploration projects, analysts undertake more private information acquisition and processing activities for these firms. The estimated coefficient on *EXPL×LRev_HExpl* is marginally significant (Coeff. = -0.295, *t*-stat. = -1.93) in the *CONSENSUS* regression in Column (1), suggesting that analysts' common and private information increases by a similar degree for non-producers. A significantly negative coefficient on *EXPL×LRev_HExpl* (Coeff. = -0.144, *t*-stat. = -2.91) in the *AFE* regression in Column (4) indicates that analysts' forecast accuracy increases with E&E expenditure by non-producers. For the other three groups, the study finds no evidence that analysts' private search activities and their forecasting ability are associated with the intensity of E&E activities.

<Insert Table 3.6 about Here>

Panel B of Table 3.6 presents two-tailed *p*-values for tests of differences across these four groups. I find that in the *COMMON* and *PRIVATE* regressions, the coefficients on *EXPL×LRev_HExpl* are statistically more positive than *EXPL×HRev_HExpl*. This suggests that analysts expend greater resources and efforts to search for private information for non-producers with limited or no product sales, relative to firms with similar levels of E&E activities but engaging in more production. It highlights that the future prospects of these non-producers are critically dependent on the success of their exploration projects, leading analysts to undertake more private information acquisition and processing activities in order to evaluate them.

3.7 Conclusion

Using a sample of the ASX listed extractive companies with reported E&E activities, this study examines the relations between the intensity of E&E activities and analysts' private information development activities and forecast performance. Specifically, the study examines whether the greater intensity of E&E activities motivates analysts to acquire and process relatively more private information to meet investor demand and whether this affects the accuracy of their forecast. This study finds that the proportion of private information contained in analysts' forecasts and the accuracy of analysts' forecasts increases with the level of E&E expenditure. The finding is consistent with the notion that the overall information environment of firms with greater exploration intensity is enriched by analysts' private information development.

This study further investigates factors associated with analysts' reliance on private information and their forecasting ability when facing the greater intensity in E&E activities. The study finds that capitalization of E&E expenditure conveys information about the future economic outcomes of exploration projects, which allows analysts to develop more private information and improve the accuracy of their forecasts. Moreover, the results reveal that the effect of exploration intensity on the analysts' information environment is more pronounced for firms with substantial E&E activities but limited or no production activities.

The results have several implications. First, because the evidence suggests that analysts reduce the high information asymmetry associated with E&E activities, investors can benefit from analysts' private information development and their improved forecasting ability. Whilst analysts' private information enriches the overall information environment of firms with greater exploration intensity, it also increases the idiosyncratic errors in the individual forecasts. However, these idiosyncratic errors are averaged out through the aggregation process of calculating the average forecast. It suggests that the average forecast should be the most useful to investors in forming expectations about the future performance of extractive companies.

Next, for firms investing in intangible assets, their future prospects tend to be more uncertain, which complicates the analysts' forecasting tasks. The findings suggest that for intangible assets with a limited scope of diversity and innovativeness, such as E&E projects, analysts are able to realise the benefits of their specialised knowledge, private information development and superior financial modelling skills to evaluate the future prospects of firms in carrying out projects at the various stages of exploration and development. They are able to provide more accurate forecasts.

This study suggests that the proportion of private information contained in analysts' forecasts arises from private information development by analysts. However, it could reflect differences in analysts' experience, expertise and optimism. As a limitation, this study does not differentiate between these two effects contributing to the level of variation in analysts' forecast performance. Future research may consider collecting data on analysts' experience in the industry, and their educational and prior industry background, notably whether have any geological or engineering education background or experience, to analyse its association with analysts' information environment and understand factors that contribute to the performance variation across analysts.

This study suggests several possible future research directions. This study examines the effect of capitalization of E&E expenditure using the area of interest accounting method on the analysts' information environment. Prior literature demonstrates different levels of value relevance using the successful efforts and full costs accounting methods in the extractive industries (Bryant, 2003). Future studies may extend this line of research to examine the impact of different accounting methods to account for E&E costs on the analysts' information environment. Moreover, as different types of intangible assets exhibit different characteristics, further studies may investigate the factors associated with analysts' ability to interpret intangibles-related information in other industries.

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Table 3.1
Descriptive Statistics

Variables	*Mean*	*Median*	*Std. Dev.*	*25%*	*75%*
CONSENSUS	0.600	0.630	0.273	0.388	0.842
PRIVATE	28.513	14.473	60.335	4.786	32.304
AFE	0.074	0.022	0.153	0.010	0.059
EXPL	0.073	0.032	0.104	0.009	0.091
SIZE	8.592	8.506	0.757	8.081	9.055
EARNCHANGE	0.110	0.031	0.297	0.012	0.075
LOSS	0.260	0.000	0.439	0.000	1.000
LEVERAGE	0.875	0.657	0.895	0.312	1.115
COVER	5.834	4.000	4.870	1.500	10.091
MB	2.670	1.979	2.401	1.287	3.164

Notes:
This table presents descriptive statistics for the final sample of 781 firm-years across fiscal years 1993–2009. Because I need calculate forecast dispersion which requires a minimum of two analysts' forecasts in each firm-year to construct Barron et al.'s (1998) measures, the sample is smaller for *CONSENSUS* and *PRIVATE*, and consists of 620 firm-years. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. *CONSENSUS* is the ratio of analysts' common information to their total information, calculated using the Barron et al. (1998) model (Proposition 1, p. 427). *PRIVATE* is the private information component in analysts' consensus, calculated using the Barron et al. (1998) model (Corollary 1, p. 428) and taking the square root. *AFE* is the absolute forecast error for year *t*, measured as the absolute value of the difference between the firm's actual and forecasted annual earnings per share for year *t*, divided by share price at the end of year *t*-1. *EXPL* is the annual E&E expenditure (capitalized E&E expenditure plus E&E expense) for year *t*-1 divided by total assets at the end of year *t*-1 (total assets is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure). *SIZE* is logarithm of market value of equity at the end of year *t*-1. *EARNCHANGE* is the absolute value of the difference between current year's actual earnings per share and last year's actual earnings per share, scaled by share price at the end of year *t*-1 (actual earnings per share is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure). *LOSS* is an indicator variable that equals one if the firm reports a loss for year *t* and zero otherwise. *LEVERAGE* is total liabilities divided by book value of equity at the end of year *t*-1 (book value of equity is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure). *COVER* is the number of analysts providing earnings forecasts for the firm for year *t*. *MB* is the market-to-book ratio at the end of year *t*-1 (book value of equity is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure).

Table 3.2
Pearson Correlation Matrix

	CONSENSUS	*PRIVATE*	*AFE*	*EXPL*	*SIZE*	*EARNCHANGE*	*LOSS*	*LEVERAGE*	*COVER*	*MB*
CONSENSUS	1.00									
PRIVATE	-0.37***	1.00								
AFE	0.25***	-0.14***	1.00							
EXPL	-0.03	0.24***	0.03	1.00						
SIZE	-0.05	-0.14***	-0.36***	-0.29***	1.00					
EARNCHANGE	0.14***	-0.09**	0.62***	0.06	-0.26***	1.00				
LOSS	0.29***	0.06	0.27***	0.34***	-0.32***	0.13***	1.00			
LEVERAGE	0.05	-0.07*	0.04	-0.18***	0.13***	0.07**	-0.03	1.00		
COVER	-0.11***	-0.11***	-0.28***	-0.30***	0.71***	-0.20***	-0.38***	0.13***	1.00	
MB	-0.03	0.11***	-0.12***	0.21***	0.17***	-0.10***	0.16***	0.38***	-0.07*	1.00

Notes:
This table presents the Pearson correlation matrix for the final sample of 781 firm-year observations across fiscal years 1993–2009. Because I need calculate forecast dispersion which requires a minimum of two analysts' forecasts in each firm-year to construct Barron et al.'s (1998) measures, the sample is smaller for *CONSENSUS* and *PRIVATE*, and consists of 620 firm-years. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. All variables are defined as in Table 3.1. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table 3.3

Regressions of properties of analysts' information environment on the exploration intensity and control variables

$$Forecast\ Property_t = \beta_0 + \beta_1 EXPL_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 EARNCHANGE_{t-1} + \beta_4 LOSS_t + \beta_5 LEVERAGE_{t-1} + \beta_6 COVER_t + \beta_7 MB_{t-1} + \varepsilon_t \quad (1)$$

	(1) *CONSENSUS*		(2) *PRIVATE*		(3) *AFE*		(4) *AFE*	
	Coeff.	*t-stat.*	*Coeff.*	*t-stat.*	*Coeff.*	*t-stat.*	*Coeff.*	*t-stat.*
Intercept	0.238	(1.39)	146.161	(3.82)***	0.347	(5.22)***	0.243	(4.90)***
EXPL	-0.233	(-1.70)*	128.798	(4.21)***	-0.151	(-3.36)***	-0.076	(-1.97)**
SIZE	0.045	(2.15)**	-14.535	(-3.09)***	-0.035	(-4.26)***	-0.027	(-4.39)***
EARNCHANGE	0.118	(1.27)	-58.750	(-2.82)***	0.283	(19.70)***	0.588	(21.75)***
LOSS	0.213	(7.26)***	-0.533	(-0.08)	0.064	(6.18)***	0.057	(6.95)***
LEVERAGE	0.018	(1.30)	-4.396	(-1.45)	0.007	(1.27)	0.001	(0.15)
COVER	-0.007	(-2.23)**	0.456	(0.64)	0.000	(-0.32)	0.001	(0.76)
MB	-0.013	(-2.61)***	2.575	(2.29)**	-0.004	(-1.72)*	-0.002	(-1.73)*
INDERROR							0.026	(5.94)***
Sample size	620		620		781		620	
Adjusted R^2	10.3%		8.2%		45.7%		61.4%	

Notes:

This table presents coefficient estimates and *t*-statistics (in parenthesis) from the regressions of properties of analysts' information environment on the exploration intensity and control variables for the final sample of 781 firm-year observations across fiscal years 1993–2009. Because I need calculate forecast dispersion which requires a minimum of two analysts' forecasts in each firm-year to construct Barron et al.'s (1998) measures, the sample is smaller for *CONSENSUS*, *PRIVATE* and *INDERROR*, and consists of 620 firm-years. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. Clustering at the firm and year level or the firm level leads to the similar inference. The subscript *t* refers to year *t*. Forecast Property refers to *CONSENSUS*, *PRIVATE* and *AFE*. *CONSENSUS* is the ratio of analysts' common information to their total information, calculated using the Barron et al. (1998) model (Proposition 1, p. 427). *PRIVATE* is the private information component in analysts' consensus, calculated using the Barron et al. (1998) model (Corollary 1, p. 428) and taking the square root. *AFE* is the absolute forecast error for year *t*, measured as the absolute value of the difference between the firm's actual and forecasted annual earnings per share for year *t*, divided by share price at the end of year *t*-1. *EXPL* is the annual evaluation and exploration (E&E) expenditure (capitalized E&E expenditure plus E&E expense) for year *t-1* divided by total assets at the end of year *t*-1 (total assets is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure). *INDERROR* is the average squared error in individual forecasts, measured using the Barron et al. (1998) model (Proposition 1, p. 427). All other variables are defined as in Table 3.1. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table 3.4
Regressions of Actual EPS for Year *t* on Actual EPS for Year *t*-1

$$Actual\ EPS_t = \beta_0 + \beta_1 Actual\ EPS_{t-1} + \varepsilon_t \qquad (2)$$

	Actual EPS$_t$					
	Low levels of E&E expenditure		Medium levels of E&E expenditure		High levels of E&E expenditure	
	Coeff.	*t-stat.*	*Coeff.*	*t-stat.*	*Coeff.*	*t-stat.*
Intercept	0.345	(5.77)***	0.059	(4.22)***	0.081	(4.41)***
Actual EPS$_{t-1}$	0.350	(10.35)***	0.743	(21.22)***	0.132	(9.53)***
Sample size	254		254		254	
Adjusted R^2	29.6%		64.0%		26.2%	
Tests of differences across groups with different levels of E&E expenditure						
F value	30.41					

Notes:
This table presents coefficient estimates and *t*-statistics (in parenthesis) from the regressions of actual EPS for year *t* on actual EPS for year *t*-1. Because prior year's Actual EPS is not available in I/B/E/S for some firm-years, the sample is slightly smaller and consists of 762 firm-years. The sample is terciled into three groups: (1) a group with low levels of E&E expenditure; (2) a group with medium levels of E&E expenditure; (3) a group with high levels of E&E expenditure. In the regression model, the subscript *t* refers to year *t*. Actual EPS$_t$ is the actual annual earnings per share for year *t*. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table 3.5
Regressions of properties of analysts' information environment on levels of capitalized and expensed E&E expenditure and control variables

$$Forecast\ Property_t = \beta_0 + \beta_1 EXPLCAP_{t-1} + \beta_2 EXPLEXPCAP_{t-1} + \beta_3 EXPLEXPEXP_{t-1} + \beta_4 SIZE_{t-1} + \beta_5 EARNCHANGE_{t-1} + \beta_6 LOSS_t + \beta_7 LEVERAGE_{t-1} + \beta_8 COVER_t + \beta_9 MB_{t-1} + \varepsilon_t \quad (3)$$

	(1) *CONSENSUS*		(2) *COMMON*		(3) *PRIVATE*		(4) *AFE*	
	Coeff.	*t-stat.*	*Coeff.*	*t-stat.*	*Coeff.*	*t-stat.*	*Coeff.*	*t-stat.*
Intercept	0.195	(1.09)	94.719	(5.32)***	139.240	(3.49)***	0.398	(5.89)***
EXPLCAP	-0.149	(-1.03)	49.801	(3.48)***	127.099	(3.96)***	-0.171	(-3.68)***
EXPLEXPCAP	-1.277	(-0.82)	-286.637	(-1.84)*	-352.250	(-1.01)	1.830	(2.98)***
EXPLEXPEXP	-0.506	(-0.46)	84.615	(0.77)	54.522	(0.22)	-0.751	(-1.88)*
SIZE	0.050	(2.31)**	-8.296	(-3.81)***	-13.599	(-2.78)***	-0.041	(-4.93)***
EARNCHANGE	0.122	(1.30)	-38.200	(-4.08)***	-54.679	(-2.60)***	0.279	(19.53)***
LOSS	0.210	(7.16)***	0.009	(0.01)	0.458	(0.07)	0.063	(6.10)***
LEVERAGE	0.019	(1.43)	-1.919	(-1.42)	-5.011	(-1.65)*	0.007	(1.29)
COVER	-0.007	(-2.29)**	-0.046	(-0.14)	0.396	(0.55)	0.000	(-0.16)
MB	-0.014	(-2.83)***	0.681	(1.36)	2.796	(2.49)**	-0.004	(-1.70)*
Sample size	620		620		620		781	
Adjusted R^2	9.9%		10.8%		7.8%		46.4%	

Notes:

This table presents coefficient estimates and *t*-statistics (in parenthesis) from the regressions of properties of analysts' information environment on levels of capitalized and expensed evaluation and exploration (E&E) expenditure and control variables for the final sample of 781 firm-year observations across fiscal years 1993–2009. Because I need calculate forecast dispersion which requires a minimum of two analysts' forecasts in each firm-year to construct Barron et al.'s (1998) measures, the sample is smaller for *CONSENSUS*, *COMMON* and *PRIVATE*, and consists of 620 firm-years. A firm-year observation is defined as a Capitalizer if in that year the firm reported capitalized E&E expenditure; otherwise the firm-year observation is classified as an Expenser. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. Clustering at the firm and year level or the firm level leads to the similar inference. The subscript *t* refers to year *t*. Forecast Property refers to *CONSENSUS*, *COMMON*, *PRIVATE* and *AFE*. *CONSENSUS* is the ratio of analysts' common information to their total information, calculated using the Barron et al. (1998) model (Proposition 1, p. 427). *COMMON* is the common information component in analysts' consensus, calculated using the Barron et al. (1998) model (Corollary 1, p. 428) and taking the square root. *PRIVATE* is the private information component in analysts' consensus, calculated using the Barron et al. (1998) model (Corollary 1, p. 428) and taking the square root. *AFE* is the absolute forecast error for year *t*, measured as the absolute value of the difference between the firm's actual and forecasted annual earnings per share for year *t*, divided by share price at the end of year *t*-1. *EXPLCAP* is the annual E&E expenditure capitalized by Capitalizers for year *t*-1 divided by total assets at the end of year *t*-1 (total assets is re-stated on an "as-if-expensing" basis for Capitalizers). *EXPLEXPCAP* is the annual E&E expenditure expensed by Capitalizers for year *t*-1 divided by total assets at the end of year *t*-1 (total assets is re-stated on an "as-if-expensing" basis for Capitalizers). *EXPLEXPEXP* is the annual E&E expenditure expensed by Expensers for year *t*-1 divided by total assets at the end of year *t* – 1. All other variables are defined as in Table 3.1. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table 3.6

Regressions of properties of analysts' information environment on the exploration intensity and control variables conditional on firms' operating activities

$$Forecast\ Property_t = \beta_0 + \beta_1 EXPL_{t-1} \times LRev\_HExpl_{t-1} + \beta_2 EXPL_{t-1} \times HRev\_HExpl_{t-1} + \beta_3 EXPL_{t-1} \times LRev\_LExpl_{t-1} + \beta_4 EXPL_{t-1} \times HRev\_LExpl_{t-1} + \beta_5 SIZE_{t-1} + \beta_6 EARNCHANGE_{t-1} + \beta_7 LOSS_t + \beta_8 COVER_{t-1} + \beta_9 LEVERAGE_{t-1} + \beta_{10} MB_{t-1} + \varepsilon_t \quad (4)$$

Panel A: Regressions of properties of analysts' information environment on the exploration intensity conditional on firms' operating activities

	(1) *CONSENSUS*		(2) *COMMON*		(3) *PRIVATE*		(4) *AFE*	
	Coeff.	*t-stat.*	*Coeff.*	*t-stat.*	*Coeff.*	*t-stat.*	*Coeff.*	*t-stat.*
Intercept	0.267	(1.52)	92.984	(5.35)***	128.938	(3.31)***	0.341	(5.03)***
EXPL × LRev_HExpl	-0.295	(-1.93)*	63.954	(4.23)***	172.297	(5.07)***	-0.144	(-2.91)***
EXPL × HRev_HExpl	-0.152	(-0.52)	-41.282	(-1.44)	-10.914	(-0.17)	-0.081	(-0.72)
EXPL × LRev_LExpl	-0.032	(-0.02)	-133.257	(-0.87)	110.633	(0.32)	0.392	(0.54)
EXPL × HRev_LExpl	-1.047	(-0.55)	365.146	(1.93)*	487.749	(1.15)	0.316	(0.48)
SIZE	0.042	(1.98)**	-8.201	(-3.88)***	-12.693	(-2.67)***	-0.035	(-4.17)***
EARNCHANGE	0.118	(1.26)	-40.489	(-4.39)***	-57.747	(-2.79)***	0.284	(19.71)***
LOSS	0.215	(7.29)***	-0.901	(-0.31)	-1.380	(-0.21)	0.064	(6.12)***
LEVERAGE	0.016	(1.19)	-1.436	(-1.06)	-3.808	(-1.25)	0.006	(1.19)
COVER	-0.008	(-2.28)**	0.258	(0.79)	0.754	(1.03)	-0.001	(-0.45)
MB	-0.012	(-2.42)**	0.397	(0.78)	2.113	(1.86)*	-0.004	(-1.66)*
Sample size	620		620		620		781	
Adjusted R^2	10.0%		12.3%		9.3%		45.5%	

Panel B: Two-tailed *p*-values for tests of differences across groups with different levels of exploration and production activities

	CONSENSUS	*COMMON*	*PRIVATE*	*AFE*
EXPL × LRev_HExpl = EXPL × HRev_HExpl	0.6222	0.0003	0.0046	0.5695
EXPL × LRev_HExpl = EXPL × LRev_LExpl	0.6885	0.1043	0.4480	0.4508
EXPL × LRev_HExpl = EXPL × HRev_HExpl	0.8639	0.1943	0.8564	0.4785
EXPL × HRev_HExpl = EXPL × LRev_LExpl	0.6333	0.0286	0.2307	0.5060
EXPL × HRev_HExpl = EXPL × HRev_LExpl	0.9353	0.5296	0.7112	0.5278
EXPL × LRev_LExpl = EXPL × HRev_LExpl	0.6456	0.0226	0.4410	0.9320

Notes:

Panel A of this table presents coefficient estimates and *t*-statistics (in parenthesis) from the regressions of properties of analysts' information environment on levels of evaluation and exploration (E&E) expenditure and control variables conditional on firms' operating activities for the final sample of 781 firm-year observations across fiscal years 1993–2009. Panel B of this table presents two-tailed *p*-values for tests of differences across groups with different levels of exploration and production activities. Because I need calculate forecast dispersion which requires a minimum of two analysts' forecasts in each firm-year to construct Barron et al.'s (1998) measures, the sample is smaller for *CONSENSUS*, *COMMON* and *PRIVATE*, and consists of 620 firm-years. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. Clustering at the firm and year level or the firm level leads to the similar inference. The subscript *t* refers to year *t*. Forecast Property refers to *CONSENSUS*, *COMMON*, *PRIVATE* and *AFE*. *CONSENSUS* is the ratio of analysts' common information to their total information, calculated using the Barron et al. (1998) model (Proposition 1, p. 427). *COMMON* is the common information component in analysts' consensus, calculated using the Barron et al. (1998) model (Corollary 1, p. 428) and taking the square root. *PRIVATE* is the private information component in analysts' consensus, calculated using the Barron et al. (1998) model (Corollary 1, p. 428) and taking the square root. *AFE* is the absolute forecast error for year *t*, measured as the absolute value of the difference between the firm's actual and forecasted annual earnings per share for year *t*, divided by share price at the end of year *t*-1. *LRev_HExpl* is an indicator variable that equals one if a firm-year observation is from the *LRev_HExpl* group. *HRev_HExpl*, *LRev_LExpl* and *HRev_LExpl* are indicator variables indicating firm-year observations from the *HRev_HExpl*, *LRev_LExpl* and *HRev_LExpl* groups. I partition sample firms into four groups based on the median values of their annual operating revenue *REV* ($112.583 million) and *EXPL* measure (0.032), where High is above or equal the median and Low is below the median: (1) Low *REV* and High *EXPL* group (*LRev_HExpl*); (2) High *REV* and High *EXPL* group (*HRev_HExpl*); (3) Low *REV* and Low *EXPL* group (*LRev_LExpl*); and (4) High *REV* and Low *EXPL* group (*HRev_LExpl*). All other variables are defined as in Table 3.1. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

4 CHAPTER FOUR

Exploration Intensity and Analyst Forecast Bias

4.1 Introduction

In the extractive industries, the inherent uncertainty and high information asymmetry associated with the prospective outcomes of exploration & evaluation (E&E) activities have long been recognized (Ferguson and Crockett, 2003; Poskitt, 2005; Bird et al., 2013). Because of the prominent role played by analysts in analyzing and interpreting information about firms and disseminating that information to investors, extractive industry investors are likely to rely on analysts' earnings forecasts to supplement company disclosures (Hirst et al., 1995; Ackert et al., 1996; Womack, 1996). Barron et al. (2002) argue that analysts' forecasts are more useful to help investors form accurate earnings expectations for firms with higher levels of intangible assets than other firms because of the inherent uncertainty about the realization of future economic benefits associated with intangible assets and analysts' ability in impounding higher proportions of private information into their forecasts. Other studies also suggest that analysts tend to issue biased forecasts for firms with uncertain information environments (Das et al., 1998; Lim, 2001; Diether et al., 2002; Beyer, 2008). Furthermore, Gu and Wang (2005) and Chen et al. (2014) provide empirical evidence that the accuracy of analysts' forecasts improves with some types of intangible assets, i.e., intangible assets subject to intangibles-related regulations in the biotech, pharmaceutical and medical equipment industries or E&E expenditure in the extractive industries. It is uncertain whether analysts who follow high-intangible firms trade off forecast bias to cultivate access to managerial information in order to facilitate their private information development and ultimately enhance their forecast accuracy. Given the rise of intangible assets in size and contribution to corporate earnings over the last two decades,[58] this study examines whether the nature and extent of the uncertainty associated with a particular type of intangible assets (i.e., E&E expenditure) is a potential determinant of bias in analysts' forecasts.

Prior research suggests that analysts expend more resources on private information development in an environment in which information asymmetry is higher and investors can derive greater benefits from it (Barth et al., 2001; Frankel et al., 2006). This effect is more pronounced for firms with higher levels of intangible assets including E&E expenditure because of the nature of the firms' assets (Barron et al., 2002; Chen et al., 2014). In the extractive industries, valuing the overall exploration and economic potential of the mineral assets requires analysts to take into account a wide range of input parameters.[59] Most of the input parameters at the exploration and evaluation phases of an exploration project involve inherent uncertainty. Over-estimation or under-estimation of the underlying geological uncertainties can augment of the overall risky nature of the asset (Bárdossy and Fodor, 2001). This uncertainty engages analysts in a constant search for information to improve their foresight and decision making.

The firm's management represents one of the most important sources of information for analysts because managers hold a key role making critical operational decisions that ultimately affect reported earnings (Hutton et al., 2012). Analysts' private

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[58] Over the past 25 years the market values of the S&P 500 companies have deviated greatly from their book values. This value gap indicates that the physical and financial accountable assets reflected on an average company's balance sheet today comprise no more than 20 percent of its true value. Research from intellectual property bank Ocean Tomo shows that a significant portion of this intangible value is represented by patented technology. In 2009 intangible assets as a proportion of total market value in the S&P 500 hit a peak of 81 percent (CIMA, 2013).

[59] These input parameters include geological setting, style of mineralization, grade-tonnage potential and regional endowment, commodity prices, metallurgy and mineability, infrastructure and access, and security of tenure and sovereign risk (Kreuzer and Etheridge, 2010).

communication with management is perceived as a very useful input to their earnings forecasts and stock recommendations (Brown et al., 2014).[60] Several studies suggest that managers benefit from meeting or beating analysts' forecasts through increases in share prices, compensation and job security (Bartov et al., 2002; Kasznik and McNichols, 2002; Mikhail et al., 2004), and reward analysts who issue beatable (pessimistic) forecasts with information (Brown and Caylor, 2005; Ke and Yu, 2006).

In order to improve access to managerial information, analysts have incentives to intentionally introduce pessimistic bias into their forecasts to curry favour with managers (Lim, 2001; Libby et al., 2008). This effect is expected to be more pronounced for firms with higher levels of E&E expenditure, for which the payoffs can be potentially large but are inherently uncertain. Analysts strive to develop private information to increase their forecast accuracy for these firms with inherent uncertainty surrounding their assets. I hypothesize that the intensity of E&E activities is positively associated with the pessimistic bias in analysts' forecasts throughout a fiscal year.

I also investigate the form of the forecast bias analysts follow to curry favour with managers for firms with high exploration intensity. Using the first and last analyst forecasts issued between current and prior year's earnings announcements, Ke and Yu (2006) identify four possible forms of forecast biases that capture the inter-temporal patterns of analysts' forecasts: the optimistic-to-pessimistic forecast bias, the optimistic-to-optimistic forecast bias, the pessimistic-to-pessimistic forecast bias, and the pessimistic-to-optimistic forecast bias. The pattern of the forecast bias which analysts are assumed to use to please management varies across studies. Some studies report that analysts incorporate optimism into their forecasts (Francis and

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[60] Regulation Fair Disclosure (Reg FD) prohibits the selective disclosure of material information by managers in private settings. But Reg FD does not prevent analysts from privately asking questions of managers to elicit "mosaic" information that is valuable only in combination with their private information (Bushee et al., 2013). Analysts can use these private communications with management to get details not explained in the financial statements or on public calls, to check the assumptions of their models, and to gain qualitative insights into the firm and its industry (Brown et al., 2014).

Philbrick, 1993; Das et al., 1998; Lim, 2001) while others suggest that analysts deliver pessimistic forecasts (Matsumoto, 2002; Burgstahler and Eames, 2006). Recent studies document an optimistic-to-pessimistic or so-called “walk-down” pattern in analysts’ forecasts from early optimism to slight pessimism just prior to the earnings announcement (Richardson et al., 2004; Ke and Yu, 2006). These studies interpret such an optimistic-to-pessimistic pattern as consistent with managers preferring forecasts that are initially optimistic but then are revised down to be pessimistic before the earnings announcement. Finally, Hilary and Hsu (2013) provide evidence that analysts strategically incorporate a pessimistic-to-pessimistic pattern into their forecasts to increase their forecast error consistency because analysts who deliver consistent forecast errors have a greater ability to affect share prices and achieve better career outcomes than those who deliver inconsistent forecast errors.[61]

I find that pessimism in analysts’ forecasts increases with the intensity of E&E activities, indicating that the effect of analysts biasing their forecasts to gain information access from managers is more pronounced for firms with higher levels of E&E expenditure. The results also suggest that analysts are more likely to follow a pessimistic-to-pessimistic pattern in response to greater exploration intensity, consistent with analysts’ strategic use of pessimistic biases to improve access to managerial information and their forecast error consistency. This study further investigates the effect of exploration intensity on analysts’ forecast biases conditional on firms’ operating activities and find that the effect of analysts issuing biased forecasts to please managers is increasing for firms that engage heavily in E&E activities relative to production activities. For these firms, their future prospects largely depend on the overall economic potential of exploration projects. Analysts strive to develop private information to be able to better incorporate and account for the high level of uncertainty surrounding these firms’ E&E activities. Since

[61] Hilary and Hsu (2013) argue that earnings forecasts issued by an analyst who delivers consistent forecast errors are more informative than those who deliver inconsistent forecast errors. Lower standard deviation of the signed forecast errors represents greater forecast error consistency.

managers are in a position to help analysts form accurate expectations of future earnings realizations (Ke and Yu, 2006), analysts are likely to accommodate managers' demand so as to curry favour.

I focus on Australia because the extractive industry is an important part of the Australian economy and the largest industry sector on the Australian Securities Exchange (ASX).[62] Analysts provide relatively extensive coverage for this sector and have strong incentives to develop their industry expertise. The ASX is one of the world's leading markets for mining and oil and gas financing,[63] with over 400 new junior resource floats during 2009 to 2013 alone (ASX, 2013b). Some of the world's largest diversified resource companies, including BHP Billiton and Rio Tinto, as well as many junior and mid-tier exploration companies are listed on the ASX. A significant majority of exploration projects is funded by equity. In particular, junior exploration companies rely on equity financing to fund exploration because most of them do not generate revenue from mining productions (SNL Metals Economics Group, 2013). The heavy reliance on equity investors to fund the capital intensive development of exploration projects makes it important for investors to understand the future implications of E&E expenditure. Investors also rely on analysts' information because of their key role in acquiring, processing, and disseminating information to capital market participants, which may increase analysts' incentives to improve management access due to competition and reputation concerns (Mayew, 2008). For these reasons, the Australian context provides a powerful setting to examine the association between the intensity of E&E activities and analyst forecast bias.

[62] The extractive industry is the nation's largest single export sector. In 2012-13, mineral and energy exports accounted for an estimated 86% (A$ 175 billion) of Australian commodity exports, and 58% of total goods and services exports (BREE, 2013). During that period, the mineral resources industries accounted for 8.6% (A$122 billion) of Australia's gross domestic product (ABS, 2013).
[63] The extractive industry is central to the ASX, with total market capitalization of $310 billion and over 1000 listed extractive companies, representing 28% of total market capitalization and 49% of all ASX listed companies by number (ASX, 2013a).

This study adds to the literature that investigates the effect of a firm's characteristic on analysts biasing their forecasts to gain information access from managers. Das et al. (1998) suggests that the firm characteristic of earnings predictability is a potential determinant of analyst forecast bias to ensure access to managerial information. Lim (2001) also predicts that analysts trade off bias to improve management access and forecast accuracy for firms with greater uncertainty about earnings or poor financial disclosures. In contrast to those studies, this research sheds some light on the effect of the nature of the firms' assets on analysts' strategic use of biases. The degree of uncertainty is greater for investments in intangible assets than other types of capital investments (Kothari et al., 2002). Analysts expend more resources and effort in developing private information for firms with higher levels of intangible assets (Barth et al., 2001; Barron et al., 2002). Their forecast accuracy improves with some types of intangible assets, i.e., intangible assets subject to intangibles-related regulations in the biotech, pharmaceutical, and medical equipment industries or E&E expenditure in the extractive industries (Gu and Wang, 2005; Chen et al., 2014). The results of this study show that the effect of analysts biasing their forecasts increases with the extentof E&E activities, consistent with analysts trading off biases to improve management access and forecast accuracy for firms with substantial uncertainties about the realization of future economic benefits associated with intangible assets.

This study also contributes to the literature that examines the effect of management's incentives on analysts' biased forecasts. Because the payoffs to E&E expenditure are highly uncertain, this uncertainty engages analysts in a constant search for information to better understand and interpret geological and other relevant data on the future prospects of E&E activities. Since managers have a central role in generating estimates of the future as they design and execute their firm's strategy, analysts' forecast biases depend on managers' incentives (Beyer, 2008). In other words, analysts are willing to accommodate managers' demands so as to curry favour (Ke and Yu, 2006; Libby et al., 2008). This study focuses on whether the nature and extent of the uncertainty associated with the firms' assets is related to analysts' strategic use of biases to please management so as to gain better information access.

Finally, with various patterns of bias in analysts' forecasts documented by prior research (Francis and Philbrick, 1993; Matsumoto, 2002; Richardson et al., 2004; Hilary and Hsu, 2013), this study investigates an inter-temporal pattern exhibited in analysts' forecasts for firms with high levels of E&E expenditure. The findings of this study suggest that analysts follow a pessimistic-to-pessimistic pattern in response to greater exploration intensity. It extends the work by Hilary and Hsu (2013) by documenting analysts' strategic use of the pessimistic biases to improve their forecast error consistency in environments with inherent uncertainty and high information asymmetry.

The remainder of the paper is organized as follows. Section 2 provides background information and reviews the related literature. Section 3 develops the hypotheses. Section 4 describes the sample selection, model specification and variable measurement. Section 5 discusses the empirical results and presents additional analysis. Section 6 concludes.

4.2 Background and Literature Review

In this section, I motivate the prediction that the nature and extent of the uncertainty associated with E&E expenditure is a potential determinant of bias in analysts' forecasts. I first establish that the inherent uncertainty and high information asymmetry associated with E&E activities create specific challenges for analysts. I then review the recent empirical evidence consistent with managers' incentives to meet or beat analysts' forecasts, and the recent literature discussing analysts' incentives to accommodate managers' demands to gain information access. Finally, I discuss the literature on analysts issuing biased forecasts in uncertain information environments.

4.2.1 Overview of the Extractive Industries

The extractive industries (comprising minerals and oil and gas) are defined as "those industries involved in finding and removing wasting natural resources located in or near the earth's crust" (IASC, 2000, p. 14). The process of exploring for and finding minerals, oil and natural gas deposits, developing those deposits and then extracting the minerals, oil and natural gas requires a long period of investment and consists of three phases of activities: exploration and evaluation, development and production.[64] The exploration and evaluation phases of an exploration project are arguably the most risky whereas a high level of uncertainty in relation to geological concepts is resolved in the development and production stages. Economic feasibility is difficult to quantify at the grassroots and early exploration stages because of the inherent uncertainty surrounding most of the input parameters used in valuing the overall exploration and economic potential of the mineral asset (Eggert, 1993).

In addition, substantial information asymmetry associated with E&E activities has long been recognized in the extractive industries (Ferguson and Crockett, 2003; Poskitt, 2005; Bird et al., 2013). Poskitt (2005) observes that extractive companies "appear to be over-represented in practices that are consistent with the existence of strong and potentially valuable information asymmetries" (p. 202). He reports excessive informational disadvantages faced by investors in extractive companies: three of the four cases of market manipulation allegations and two of the four cases of insider trading allegations by the Australian Securities and Investments Commission (ASIC) between July 1997 and June 2002 were made against extractive

[64] Exploration is the detailed examination of a geographical area of interest that has shown sufficient mineral-producing potential to merit further exploration. Exploration activities include: conducting topographical, geological, geochemical and geophysical studies; and carrying out exploratory drilling, trenching and sampling activities. Evaluation activities involve determining the technical feasibility and commercial viability of mineral deposits that have been found through exploration. Development is the establishment of access to the mineral reserve and other preparations for commercial production. Development activities often continue during production. Production involves the extraction of the natural resources from the earth and the related processes necessary to make the produced resource marketable or transportable (IASB, 2010).

companies.[65] Ferguson and Crockett (2003) and Bird et al. (2013) conclude that investors who have little geological expertise may rely more on media reports or exploration announcements with positive adjectives because of the complexity of geological information.[66] Taken together, high information asymmetry and inherent uncertainty associated with E&E activities create specific challenges for analysts to evaluate future prospects of firms with greater exploration intensity.

4.2.2 Management's Incentives to Meeting or Beating Analysts' Forecasts

Analysts rely on numerous sources of information in forming their forecasts, and one of the most important sources is the management of the firm itself. Managers are insiders who run the firm and make key business decisions, and they have an information advantage over analysts because their intimate knowledge of the firm's business strategy and its daily transactions ultimately affect reported earnings (Hutton et al., 2012). Prior literature suggests that managers have strong incentives to meet or beat analysts' forecasts because they can benefit from increases in share price, compensation and job security, and they reward analysts with information who facilitate this pattern. For example, Skinner and Sloan (2002) show that a failure to meet or beat analysts' forecasts causes a large negative share price response, which is more pronounced for growth firms. Graham et al. (2005) provide survey evidence suggesting that managers perceive large market penalties to missing earnings targets. These market penalties can provide managers with strong incentives to avoid negative earnings surprises by manipulating earnings or managing analysts' expectations. Their study finds that many managers would even reject a positive NPV (net present value) project in order to meet the next period's analyst earnings estimate. Indeed, Bartov et al. (2002) find that firms that meet or beat analysts' forecasts earn higher stock returns than those that fail to meet analysts' expectations,

[65] Market manipulation allegations were made against Reef Mining NL, Diversified Mineral Resources NL and Diamond Rose NL. Insider trading allegations were made against Mt Kersey Mining NL and Carpenter Pacific Resources NL.

[66] Ferguson and Crockett (2003, p. 103) point out that in routine mining company disclosures, "discussion of complex variables such as metal purity, the width of the drilling intercepts, and the depth below the surface where the intercept occurs" are included. "Highly technical factors including the geochemical composition of the mineralisation of the discovery" and "other complexities" could also be added.

and that these returns are not economically affected by whether the firm achieves this by managing earnings or analysts' expectations. Similarly, Kasznik and McNichols (2002) find that the market assigns a higher value to firms that consistently meet analyst expectations (over three years), after controlling for the firm's fundamental value. Finally, Brown and Caylor (2005) find that managers consider it more important to avoid negative earnings surprises than to avoid reporting losses or earnings decreases. These studies suggest that managers derive benefits from meeting or beating analyst forecasts and have strong incentives to make analyst forecasts more attainable.

4.2.3 Analysts' Incentives to Issue Biased Forecasts

Anticipating management's incentives, analysts vary their forecast biases according to managers' reporting behaviour (Beyer, 2008). One reason given for analysts issuing biased forecasts is that they have incentives to please firm management. The assumed form of bias in analysts' forecasts varies across studies. The early literature documents an optimistic bias in analysts' forecasts (Francis and Philbrick, 1993; Das et al., 1998; Lim, 2001). These studies suggest that analysts incorporate optimism into their forecasts in order to maintain good relationships with management. Other studies provide evidence that analysts induce a pessimistic bias in their forecasts to curry favour with managers who avoid reporting earnings lower than analysts' forecasts (Matsumoto, 2002; Burgstahler and Eames, 2006). More recent studies document an optimistic-to-pessimistic pattern in both analyst annual and quarterly forecasts, that is, optimism in analysts' forecasts declines through the fiscal period, and their forecasts become more pessimistic prior to the earnings announcement forecasts (Richardson et al., 2004; Cotter et al., 2006). Ke and Yu (2006) find that analysts who follow the optimistic-to-pessimistic forecast pattern are ultimately more accurate and less likely to experience job turnover. They interpret their results as consistent with analysts biasing their forecasts to obtain information from management.

Recent studies have attempted to reconcile the incentives and forecasting strategies of analysts with management's reporting incentive to achieve a positive earnings surprise, by providing evidence that managers indeed provide more or less information to analysts based on whether analysts offer forecasts that are easy to meet or beat (i.e., pessimistic forecast bias) or how favourably they view the firm. In an experimental setting, Libby et al. (2008) report that analysts are aware of a general downward bias in management earnings guidance and are likely to incorporate this pessimistic bias into their forecasts because it benefits their future relationships with management. In their study, the analysts explicitly cite that a firm's earnings conference call participation and information access are the major benefits from maintaining good relationships with management. Their results are consistent with other findings related to management discrimination among analysts based on the favour of their recommendations. Chen and Matsumoto (2006) and Mayew (2008) find analysts issuing more favourable recommendations experience a greater increase in their forecast accuracy and in the probability of participating in an earnings conference call compared with analysts with less favourable recommendations, which is consistent with analysts receiving relatively more managerial information following the issuance of more favourable recommendations. Anticipating managers' strategic reporting behaviour, analysts are more likely to introduce pessimistic bias into their forecasts. This study focuses on whether the nature and extent of the uncertainty associated with intangible assets motivate analysts to obtain better access to managerial information as evidenced by their strategic use of biases in their forecasts.

4.2.4 Analysts' Forecasts and Intangible Assets

Prior research suggests that analysts have incentives to search for private information in an environment where information asymmetry is pronounced and investors can derive greater benefits from it (e.g., Barth et al., 2001; Barron et al., 2002; Frankel et al., 2006). Barth et al. (2001) suggest that analysts expend more resources collecting and analyzing information for firms with higher levels of intangible assets. Barron et al. (2002) document that analysts supplement firms' financial information by placing relatively greater reliance on their private information when deriving earnings forecasts for firms with significant intangible assets. Indeed, Chen et al. (2014) find that the proportion of private information contained in analysts' forecasts increases with E&E expenditure, consistent with analysts increasing their private information gathering efforts in response to the greater intensity of E&E activities. Taken together, analysts' private information plays a vital role in evaluating future prospects of firms with uncertain information environments.

Analysts may trade off bias to gain information access from managers. Early empirical work by Das et al. (1998), Lim (2001) and Diether et al., (2002) provides evidence that firms with more uncertain information environments are associated with more optimistically biased forecasts. Das et al. (1998) focus on whether the firm characteristic of earnings predictability is associated with analyst forecast bias and find that analysts' forecasts contain significantly more optimistic bias for firms characterized by lower earnings predictability. Using firm size and analyst coverage to proxy for the richness of a firm's information environment, and stock return volatility to proxy for firm specific uncertainty, Lim (2001) finds that analyst forecast bias increases with firm information uncertainty, suggesting that analysts are likely to trade off bias to gain information access for firms with uncertain information environments. Diether et al. (2002) use dispersion in analysts' forecasts to measure uncertainty surrounding a firm's earnings prospects and further confirm that there is a strong positive relationship between optimism in analysts' forecasts and firms with uncertain information environments. Because the degree of uncertainty is greater for investments in intangible assets than other types of capital investments (Kothari et al., 2002), this study examines whether the nature of the firms' assets is associated with analysts' forecast biases. Furthermore, with an apparent shift of the form of the forecast bias analysts use to curry favour with managers as discussed in section 4.2.3, this study also investigates the inter-temporal pattern of analysts' forecasts for firms carrying substantial levels of intangible assets.

4.3 Hypothesis Development

Prior research suggests that analysts expend more resources and efforts acquiring and developing private information for firms with higher levels of intangible assets including E&E expenditure because of the nature and extent of the uncertainty associated with the intangible assets (Barron et al., 2002; Chen et al., 2014). Specifically, in the extractive industries, the interpretation and evaluation of prospective outcomes of E&E activities requires analysts to take into account a wide range of parameters that are relevant to determine the overall exploration and economic potential of the mineral asset (Kreuzer and Etheridge, 2010). Given the inherent uncertainty surrounding most of these input parameters, analysts need to gather information from numerous sources to be able to better understand and interpret geological and other relevant data.

The firm’s management represents one of the most important sources of information for analysts because managers have intimate knowledge of the firm’s business strategy and hold a key role making critical operational decisions that ultimately affect reported earnings (Hutton et al., 2012). Prior literature suggests that managers have incentives to report earnings that meet or exceed analysts’ forecasts. In anticipating management’s reporting incentives, analysts may incorporate a pessimistic bias into their forecasts to help managers beat those forecasts. In doing so, analysts can curry favour with managers, leading to better access to managerial information (Lim, 2001; Libby et al., 2008).

This effect is expected to be more pronounced for firms with higher levels of E&E expenditure, namely junior exploration companies. Information asymmetry is arguably higher for junior exploration companies compared to established mining companies given the absence of an established earnings history (Ferguson and Crockett, 2003). Junior exploration companies typically have highly uncertain earnings potential with little or no past or current earnings or positive cash flows to indicate their potential (Iddon et al., 2013). Hence, reported earnings may be less useful for assessments of the future prospects of such firms with greater exploration intensity, causing analysts to seek and process private information. For these exploration companies, the risks and uncertainties of their exploration projects are critical to their very existence, as the continuation of these companies as a going concern is closely tied to the successful delineation and extraction of economic deposits. Their management and directors are likely to be better informed than outside investors on technical and commercial aspects of these exploration projects and associated exploration and development risks. Ferguson et al. (2011) argue that higher director ownership may signal positive private information, and higher information asymmetry may allow large director shareholdings to more effectively expropriate wealth from outside investors for junior exploration companies. The IPO underpricing phenomenon among junior exploration companies further confirm the considerable information asymmetry between firm management and outside investors (Givoly and Shi, 2008). Currying favour with "informed parties" such as management certainly gives analysts edge to gain insights on the future outlook of these firms. Analysts can use communications with management to get details not explained in the financial statements or on public calls, to check the assumptions of their models, and to gain qualitative insights into the firm and its industry (Brown et al., 2014). My first hypothesis, stated in the alternate form, is:

H1: *The pessimistic bias in analysts' forecasts throughout a fiscal year is more pronounced for firms with greater exploration intensity.*

Hilary and Hsu (2013) find that analysts introduce a systematic bias into their forecasts to increase the consistency of their forecast performance. This is because analysts who demonstrate forecast error consistency have greater ability to affect share prices, which has consequences for these analysts' careers: they are less likely to be demoted to less prestigious brokerage houses and are more likely to be rewarded with greater professional recognition. The evidence in Hilary and Hsu (2013) suggests that analysts who strategically follow a pessimistic-to-pessimistic pattern are likely to win favour from managers and secure better career outcomes. The effect is expected to be more pronounced for the firms with substantial uncertainties surrounding their E&E expenditure. My second hypothesis, stated in the alternate form, is:

H2: *A pessimistic-to-pessimistic pattern in analysts' forecasts within a fiscal year is more pronounced for firms with greater exploration intensity.*

4.4 Research Design

4.4.1 Sample

Data on one-year ahead analysts' forecasts of annual earnings per share (EPS) and the corresponding actual earnings are obtained from the I/B/E/S International Summary file. Financial statement data are sourced from the Morningstar DataLink database. Share prices and market capitalization information are sourced from the CRIF Share Price and Price Relative (SPPR) database. As noted in section 4.4.2, I manually collect annual E&E expenditure data from the ASX-listed extractive companies' financial statements through the Morningstar DatAnalysis database.

The initial sample includes 7,331 firm-year monthly forecast observations containing E&E expenditure in annual reports or for which E&E expenditure can be estimated using other financial statement line items for the period between the fiscal years 1993 and 2009, with consensus forecasts issued between the prior and current year's earnings announcements. To control for potential outliers, the absolute value of price-deflated forecast errors that are greater than 100% are excluded (Richardson et al., 2004). This requirement reduces the sample by 315 observations. The final sample consists of 7,016 firm-year monthly forecast observations, representing 794 firm-years and 167 unique firms. The sample for *PESSPTN* is further reduced to 705 firms-years if only the observations with four possible forms of analyst forecast bias as defined in section 4.4.4 are retained.

4.4.2 Proxy for the Intensity of E&E Activities

Similar to the measures of R&D intensity of Aboody and Lev (1998) and Oswald and Zarowin (2007), I use the annual E&E expenditure (capitalized E&E expenditure plus E&E expense) scaled by total assets as a proxy for the intensity of E&E activities. Reported financial numbers for firms that capitalize E&E expenditure are re-stated to be on an "as-if-expensing" basis, so earnings and other related accounting numbers between firms that capitalize E&E expenditure and firms that expense their E&E outlays when incurred are comparable (Oswald and Zarowin, 2007).[67] High levels of scaled E&E expenditure indicate a greater intensity of E&E activities.

Reviewing the ASX-listed extractive companies' financial statements from the ASPECT Annual Reports Online website, I manually collect E&E expense and capitalized E&E expenditure data from both the income statement and the statement of financial position. If a firm capitalizes E&E expenditure, it reports capitalized E&E expenditure in the notes to the statement of financial position. If a firm does not report capitalized E&E expenditure directly, I estimate it using other financial statement line items.[68]

4.4.3 Measuring Analyst Forecast Bias

Consistent with Richardson et al. (2004), analyst forecast bias (BIAS) is measured as the signed forecast error, that is, the difference between actual earnings and consensus forecasts, scaled by share price:

$$\text{BIAS}_{i,t,m} = (\text{Actual EPS}_{i,t} - \text{Consensus EPS Forecast}_{i,t,m}) / \text{Price}_{i,\,t\text{-}1}$$

[67] For firms that capitalize E&E expenditure, their total assets on an "as-if-expensing" basis are estimated by subtracting the amount of E&E assets from reported total assets.

[68] For example, capitalized E&E expenditure is estimated by subtracting the amount of impairment loss for E&E assets, the amount of E&E assets written off, the amount of E&E assets disposed, the amount of E&E assets transferred to other accounts, and also subtracting the opening balance of E&E assets from the closing balance of E&E assets. If the value of estimated capitalized E&E expenditure is negative, the firm-year observation is excluded. There are 42 firm-year observations with a negative value of estimated capitalized E&E expenditure.

where Actual $EPS_{i,t}$ is the actual I/B/E/S annual earnings per share for firm *i* in year *t*, and Consensus EPS $Forecast_{i,t,m}$ is the I/B/E/S one-year ahead mean consensus forecast for firm *i* and year *t* in month *m*. Month *m* refers to the number of months following the prior year's earnings announcement. For example, month $m = 1$ is the first month following the prior year's earnings announcement, month $m = 2$ is the second month following the prior year's earnings announcement, and so on. $Price_{i,\,t\text{-}1}$ is the share price of firm *i* in month 1. A negative value of BIAS implies an optimistic forecast, whereas a positive value implies a pessimistic forecast.

4.4.4 Model Specification and Variable Measurement

Following Richardson et al. (2004), I construct three alternative dependent variables to test for a relationship between the intensity of E&E activities and analyst forecasts bias: the continuous measure of the signed forecast error, *BIAS*, the indicator variable for analyst pessimism, *PESSBIAS*, and the indicator variable for the pessimistic-to-pessimistic pattern in analysts' forecasts, *PESSPTN*. The tests are based on the following regression equations (all variables are calculated each year for each firm, and the firm subscript is suppressed):

$$\begin{aligned} BIAS_{t,m} &= \beta_0 + \beta_1 EXPL_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 COVER_t \\ &\quad + \beta_4 EARNCHANGE_{t-1} + \beta_5 LOSS_t + \beta_6 MB_{t-1} \\ &\quad + \beta_7 MONTH_t + \beta_8 YEAR_t + \varepsilon_t \end{aligned} \tag{1}$$

$$\begin{aligned} PESSBIAS_{t,m} &= \beta_0 + \beta_1 EXPL_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 COVER_t \\ &\quad + \beta_4 EARNCHANGE_{t-1} + \beta_5 LOSS_t + \beta_6 MB_{t-1} \\ &\quad + \beta_7 MONTH_t + \beta_8 YEAR_t + \varepsilon_t \end{aligned} \tag{2}$$

$$\begin{aligned} PESSPTN_t &= \beta_0 + \beta_1 EXPL_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 COVER_t \\ &\quad + \beta_4 EARNCHANGE_{t-1} + \beta_5 LOSS_t + \beta_6 MB_{t-1} \\ &\quad + \beta_7 YEAR_t + \varepsilon_t \end{aligned} \tag{3}$$

where the subscript *t* refers to year *t*, and the subscript *m* refers to month *m*. *BIAS* is defined as in section 4.4.3. *PESSBIAS* is an indicator variable coded one if *BIAS* is greater than or equal to zero, and zero otherwise. *PESSPTN* is an indicator variable equal to one if analysts follow the pessimistic-to-pessimistic forecast pattern (that is, $BIAS_{first}$, the first forecast in fiscal year and $BIAS_{last}$, the last forecast in the final month before the earnings announcement are pessimistic, $BIAS_{first} \geq 0$ and $BIAS_{last} \geq 0$). *PESSPTN* is coded zero if analysts follow the optimistic-to-pessimistic forecast pattern (that is, the first forecast in a fiscal year is optimistic but the last forecast in the final month before the earnings announcement is pessimistic, $BIAS_{first} < 0$ and $BIAS_{last} \geq 0$), or if analysts follow the optimistic-to-optimistic forecast pattern (that is, both the first and the last forecasts are optimistic, $BIAS_{first} < 0$ and $BIAS_{last} < 0$), or analysts follow the pessimistic-to-optimistic forecast pattern (that is, analysts switch from initial pessimism to later optimism, $BIAS_{first} \geq 0$ and $BIAS_{last} < 0$). This variable is coded as missing for firm-years where the last forecast is the same as the first forecast. *EXPL* is the annual E&E expenditure (capitalized E&E expenditure plus E&E expense) for year *t*-1 divided by total assets at the end of year *t*-1.[69] The ordinary least squares (OLS) pooled cross-sectional regression is used when *BIAS* is the dependent variable, and the logistic cross-sectional regression is used when *PESSBIAS* or *PESSPTN* is the dependent variable.

A set of control variables that might affect analyst forecast bias is included in the regressions: firm size, analyst coverage, change in earnings, losses, and market-to-book ratio. The general information environment is likely to be richer for firms that are larger and followed by more analysts, potentially affecting analyst forecast bias (Das et al., 1998; Lim, 2001). Herrmann et al. (2008) and Keskek and Tse (2013) further suggest that analysts tend to be more pessimistic in rich information environments. Thus, I control for firm size (*SIZE*) and analyst coverage (*COVER*) in the analyses, using the logarithm of market value of equity at the end of year *t*-1 and the number of analysts providing earnings forecasts for the firm for year *t*. Duru and

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[69] Total assets are re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure.

Reeb (2002) suggest that the change in earnings affects analysts' forecasts. A control for earnings change (*EARNCHANGE*) is therefore included in the regressions, using the absolute value of the difference between current and prior year actual earnings per share divided by share price at the end of year *t*-1.[70] Brown (2001) finds that analysts, on average, issue more optimistic forecasts for loss firms. To control for the effect of losses, an indicator variable (*LOSS*), coded one if the firm reports a loss for year *t* and zero otherwise, is included. Prior research finds that managers in growth firms are relatively more likely than managers of value firms to make analyst forecasts more attainable to meet or beat (Brown, 2001; Richardson et al., 2004). To control the influence of managers in growth firms on analyst forecasts, the market-to-book ratio (*MB*) at the end of fiscal year *t*-1 is included.[71]

Consistent with Richardson et al. (2004), I include two additional variables to capture possible changes in analyst pessimism over the forecast horizon and year trend. *MONTH* is the number of months between the prior year's earnings announcement and the consensus forecast. For example, *MONTH* = 1 is the first month following the prior year's earnings announcement when a forecast is made, *MONTH* = 2 is the second month following the prior year's earnings announcement when a forecast is made, and so on.[72] *MONTH* is increasing in closeness to the earnings announcement. *YEAR* is the year trend in forecast bias, measured as the difference between the year of the forecast and the base year 1993 (the first year in the sample).

H1 predicts that the intensity of E&E activities is positively associated with analyst pessimism. If the relations between *BIAS* and *EXPL*, and *PESSBIAS* and *EXPL* are estimated to be positive, H1 is supported. H2 predicts a positive relationship between

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[70] Actual earnings per share is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure.
[71] Book value of equity is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure.
[72] *MONTH* is included in the equation (1) and (2) to examine the impact of forecast horizon on analyst pessimism.

the pessimistic-to-pessimistic analyst forecast pattern and the intensity of E&E activities, an estimated positive coefficient on *EXPL* supports H2.

4.5 Empirical Results

4.5.1 Descriptive Statistics

Table 4.1 presents descriptive statistics relating to the distribution of regression variables. All continuous variables are winsorized at the 1% and 99% levels. $BIAS_{first}$ and $BIAS_{last}$, the earliest and latest forecasts before the earnings announcement in a fiscal year are optimistically biased on average, consistent with analyst issuing optimistic forecasts in uncertain information environments (Das et al., 1998; Lim, 2001; Diether et al., 2002). On average, 41.8% of the last forecasts before the earnings announcement are pessimistically biased and 24% of analyst forecasts follow the pessimistic-to-pessimistic forecast pattern.[73] The mean (median) of EXPL is 0.076 (0.033), with a standard deviation of 0.108, indicating that on average (at the median) the extractive companies with analyst coverage invest 7.4% (3.2%) of total assets in E&E activities with a high variation across the sample firms. The mean value is more than twice the size of the median value, consistent with the concentration of intensive E&E activities in certain firms.

<Insert Table 4.1 about Here>

The sample firms are covered by 6 (4) analysts on average (at the median). The median firm has a log market value of equity of \$19.571, equivalent to market value of \$316 million, and makes profits with earnings growth of 3.1% and a market-to-book ratio of 2.035. It is consistent with large and profitable firms attracting analyst following.

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[73] Consistent with Ke and Yu (2006), the most common form of forecast bias is the optimistic-to-optimistic pattern (48%), followed by pessimism-to-pessimism (24%), optimistic-to-pessimistic (19%), and pessimistic-to-optimistic patterns (9%) in the sample (untabulated).

Table 4.2 presents the Pearson correlations among the variables. It shows that *EXPL* is negatively related to *SIZE* and *COVER*, consistent with junior exploration companies with few analysts following playing a critical role in investing in exploration projects to find new assets (PriceWaterhouseCoopers, 2013). Moreover, *EXPL* is positively associated with *LOSS* and *MB*, indicating that greater E&E intensity represents growth opportunities but high potential of making losses.

<Insert Table 4.2 about Here>

4.5.2 Regression Results

Table 4.3 presents evidence on H1 from regressions of analyst forecast bias on the exploration intensity and control variables. Panel A reports results when the continuous measure of the signed forecast error, *BIAS*, is the dependent variable and the OLS pooled cross-sectional regression is run. The estimated coefficient on *EXPL* is significantly positive at 0.2 (*t*-stat. = 11.839), indicating that as the levels of E&E expenditure increase, analysts' forecasts become more pessimistic. The estimated effect of the increasing intensity of E&E activities on the pessimism in analysts' forecasts appears to be economically significant. All else constant, a firm that experiences one-standard-deviation increase in the exploration intensity would beat analyst forecasts by an average of 2% of its share price (0.2×0.108).

<Insert Table 4.3 about Here>

A similar result is obtained in Panel B when the dependent variable is an indicator variable for the pessimism in analysts' forecasts, *PESSBIAS*, and the logistic pooled cross-sectional regression is performed. *EXPL* is significantly positive (Coeff. = 1.493, *z*-stat. = 4.545), indicating a positive association between the intensity of E&E activities and pessimism in analysts' forecasts. When using the log odds ratio to interpret, all else constant, the odds of having a pessimistic forecast error rises by 37.3% for a one-standard-deviation increase in the intensity of E&E activities (($e^{1.493}$-1)×0.108). In summary, *EXPL* is highly statistically significant in the predicted direction in both *BIAS* and *PESSBIAS* regressions where the measure of analyst forecast bias is continuous or binary. The results support H1 and suggest that pessimism in analysts' forecasts increases with the intensity of E&E activities, consistent with analysts biasing their forecasts to gain information access from managers particularly for firms with high levels of E&E expenditure.

The results in Table 4.3 also corroborate a downward bias in analysts' forecasts. The significantly positive coefficient in both *BIAS* and *PESSBIAS* regressions on *MONTH* indicates that analyst pessimism increases as the forecast horizon shortens towards the earnings announcement, consistent with analysts collaborating with managers to walk down earnings expectations (Matsumoto, 2002; Richardson et al., 2004; Cotter et al., 2006). The significantly positive coefficient on *YEAR* in both regressions indicates that the tendency of analysts' issuing pessimistic earnings forecasts for firms with greater exploration intensity has increased over time from the 1990s to the 2000s.

Other regression coefficients are generally statistically significant in the predicted directions. Consistent with Brown (2001), the coefficient on *LOSS* is significantly positive in both *BIAS* and *PESSBIAS* regressions, indicating that analysts tend to issue optimistic forecasts for firms reporting losses. A significantly positive coefficient on *SIZE* in the *BIAS* regression is consistent with analyst pessimism in rich information environments (Herrmann et al., 2008; Keskek and Tse, 2013). *MB* has a significantly negative coefficient in the *PESSBIAS* regression, suggesting that analysts tend to be more optimistic for growth firms.

Table 4.4 reports the results of estimating equation (3), where the probability of analysts exhibiting the pessimistic-to-pessimistic pattern is regressed on the exploration intensity and control variables. Consistent with my prediction, the estimated coefficient on *EXPL* is significantly positive at the less than 10% level (Coeff. = 2.329, *z*-stat. = 1.891), suggesting a positive relationship between the levels of E&E expenditure and a pessimistic-to-pessimistic pattern in analysts' forecasts. Alternatively stated, all else constant, the log odds ratio of analysts following a pessimistic-to-pessimistic pattern rises by 100% (($e^{2.329}$-1)×0.108) when a firm experiences one-standard-deviation increase in the exploration intensity. The results suggest that analysts intentionally incorporate a systematic and pessimistic bias into their forecasts to access better information from management and increase their forecast error consistency. The statistically significant result for *LOSS* indicates analysts' optimism for loss-making firms (Brown, 2001).

<Insert Table 4.4 about Here>

4.5.3 Robustness Check

The cross-sectional regressions presented in Table 4.3 are estimated using a pooled sample of monthly analyst consensus forecasts for the period from 1993 to 2009 (7,016 firm-year monthly observations). To examine the impact of forecast horizon on analyst pessimism, the pooled sample includes multiple firm observations for each firm-year. This may raise a concern of dependence in the data. The inclusion of the fixed effects forecast horizon variable *MONTH* may only partially address this dependence (Richardson et al., 2004). Therefore, as an additional robustness check on the regression specification, I run regressions using only one (the final) forecast for each firm-year. *MONTH* is excluded from this specification (as there is only one observation per firm-year). The results from this reduced sample of 794 firm-years yield similar results for the *BIAS* regression (Coeff. = 0.182, *t*-stat. = 3.78).

4.5.4 Additional Analysis

The effect of increasing intensity of E&E activities on analyst forecast bias may vary between firms that engage primarily in E&E activities and those with substantial production activities. If analysts intentionally induce a pessimistic bias in their forecasts in response to the greater intensity of E&E activities, I expect that the effect of analysts biasing their forecasts to gain information access from managers is more pronounced for firms that heavily engage in E&E activities. The future prospects of these firms largely depend on the economic outcomes of exploration projects. Most of the input parameters required in the evaluation process at the exploration and evaluation phases of an exploration project are associated with inherent uncertainty. Analysts strive to develop more private information to be able to better evaluate the future prospects of these firms. Since managers are in a position to help analysts form accurate expectations of future earnings realizations (Ke and Yu, 2006), analysts are likely to accommodate managers' demands so as to curry favour.

The sample firms is partitioned into four groups based on the median values of their annual operating revenue *REV* ($108.916 million) and *EXPL* measure (0.033), where High is above or equal the median and Low is below the median:

(1) Low *REV* and High *EXPL* group (*LRev_HExpl*)	(2) High *REV* and High *EXPL* group (*HRev_HExpl*)
(3) Low *REV* and Low *EXPL* group (*LRev_LExpl*)	(4) High *REV* and Low *EXPL* group (*HRev_LExpl*)

There are 264 firm-years in each of the *LRev_HExpl* and *HRev_LExpl* groups with 2058 and 2561 monthly forecast observations respectively. Each of the *HRev_HExpl* and *LRev_LExpl* groups has 133 firm-years with 1301 and 1096 monthly forecast observations respectively. The descriptive statistics on firm characteristics of these four groups (untabulated) reveals that firms in the *HRev_LExpl* group are significantly larger than those in the other three groups, invest less in exploration projects (1.1% of total assets on average) and are followed by more analysts (10 analysts at the median). The *HRev_LExpl* group comprises largely production companies. Firms included in the *LRev_HExpl* group are smaller, spend heavily on explorations (17.1% of total assets on average), and have lower analyst coverage (two analysts at the median). The *LRev_HExpl* group consists of firms that engage primarily in E&E activities. I compare the effect of levels of E&E expenditure on analyst forecast bias for each of the four groups using the following equation:

$$
\begin{aligned}
BIAS_{t,m} = {} & \beta_0 + \beta_1 EXPL_{t-1} \times LRev\_HExpl_{t-1} + \beta_2 EXPL_{t-1} \times HRev\_HExpl_{t-1} \\
& + \beta_3 EXPL_{t-1} \times LRev\_LExpl_{t-1} + \beta_4 EXPL_{t-1} \times HRev\_LExpl_{t-1} \\
& + \beta_5 SIZE_{t-1} + \beta_6 COVER_{t-1} + \beta_7 EARNCHANGE_{t-1} + \beta_8 LOSS_t \\
& + \beta_9 MB_{t-1} + \beta_{10} MONTH_t + \beta_{11} YEAR_t + \varepsilon_t \qquad (4)
\end{aligned}
$$

$$
\begin{aligned}
PESSBIAS_{t,m} = {} & \beta_0 + \beta_1 EXPL_{t-1} \times LRev\_HExpl_{t-1} + \beta_2 EXPL_{t-1} \times HRev\_HExpl_{t-1} \\
& + \beta_3 EXPL_{t-1} \times LRev\_LExpl_{t-1} + \beta_4 EXPL_{t-1} \times HRev\_LExpl_{t-1} \\
& + \beta_5 SIZE_{t-1} + \beta_6 COVER_{t-1} + \beta_7 EARNCHANGE_{t-1} + \beta_8 LOSS_t \\
& + \beta_9 MB_{t-1} + \beta_{10} MONTH_t + \beta_{11} YEAR_t + \varepsilon_t \qquad (5)
\end{aligned}
$$

where the subscript *t* refers to year *t*, the subscript *m* refers to month *m*; *LRev_HExpl* is an indicator variable that equals one if a firm-year observation is from the *LRev_HExpl* group; *HRev_HExpl*, *LRev_LExpl* and *HRev_LExpl* are indicator variables indicating firm-year observations from the *HRev_HExpl*, *LRev_LExpl* and *HRev_LExpl* groups; and the control variables are the same as in equation (1).

If the effect of increasing exploration intensity on analyst forecast bias is greater for firms with substantial E&E activities, the coefficient on the interaction term *EXPL×LRev_HExpl* is expected to be positive in the *BIAS* and *PESSBIAS* regressions to reflect that analysts' pessimism increases with the levels of E&E expenditure for firms that heavily engage in E&E activities.

Panel A of Table 4.5 reports the results of estimating equation (4). The coefficient of interest is on *EXPL×LRev_HExpl*, which captures the effect of exploration intensity on analyst forecast bias for firms engaging in substantial E&E activities. The estimated coefficient on *EXPL×LRev_HExpl* is positive and statistically significant (Coeff. = 0.202, *t*-stat. = 10.689), indicating that the pessimism in analysts' forecasts increases with the intensity of E&E activities for firms that heavily engage in E&E activities. Because the future prospects of these exploration firms largely depend on the economic outcomes of their exploration projects, analysts intentionally induce pessimistic bias in their forecasts to curry favour with managers, with the goal of gaining better managerial information access. The estimated coefficient on

EXPL×HRev_HExpl is also significantly positive (Coeff. = 0.168, *t*-stat. = 4.284), suggesting that the level of E&E expenditure is a key factor driving the pessimism in analysts' forecast even for exploration firms that generates revenues from their productions.

<Insert Table 4.5 about Here>

A similar result is obtained in panel B when the dependent variable is an indicator variable for pessimism in analysts' forecasts, *PESSBIAS,* and the logistic pooled cross-sectional regression is performed. *EXPL×LRev_HExpl* is significantly positive (Coeff. = 1.456, *z*-stat. = 3.979), indicating a positive association between the intensity of E&E activities and analysts' pessimism. When using the log odds ratio to interpret, all else constant, the odds of having a pessimistic forecast error rises by 35.5% for a one-standard-deviation increase in the intensity of E&E activities (($e^{1.456}$-1)×0.108) for exploration firms engaging in substantial E&E activities. In summary, *EXPL×LRev_HExpl* is highly statistically significant in both *BIAS* and *PESSBIAS* regressions where the measure of analyst forecast bias is continuous or binary. I find no evidence that the pessimism in analysts' forecasts is associated with the intensity of E&E activities for firms with largely production activities. The coefficients on *EXPL×LRev_LExpl* and *EXPL×HRev_LExpl* are not statistically significant in any regression. The results suggest that analysts intentionally induce a pessimistic bias in their forecasts in response to the greater intensity of E&E activities, and this effect of analysts biasing their forecasts to gain information access from managers is more pronounced for firms that heavily engage in E&E activities.

4.6 Conclusion

The inherent uncertainty and high information asymmetry associated with the prospective outcomes of E&E activities create specific challenges for analysts. Using a sample of the ASX-listed extractive companies with reported E&E activities, this study examines whether the nature and extent of the uncertainty associated with E&E expenditure is a potential determinant of bias in analysts' forecasts, and also investigates an inter-temporal pattern of analysts' forecasts for firms with substantial E&E activities. The results suggest that the pessimistic bias in analysts' forecasts increases with the extent of E&E activities, indicating that the effect of analysts biasing their forecasts to cultivate information access from managers is more pronounced for firms with higher levels of E&E expenditure.

The results also suggest that analysts are more likely to follow a pessimistic-to-pessimistic pattern in response to greater exploration intensity, consistent with analysts' strategically biasing their forecasts pessimistically to access better information from management and increase their forecast error consistency. This study further investigates firms' operating activities associated with the effect of exploration intensity on analysts' forecast biases. The results reveal that the effect of analysts' issuing biased forecasts to please managers is greater for firms that heavily engage in E&E activities relative to production activities.

An understanding of factors affecting analysts' strategic behaviour in the context of the nature of the firms' assets is important since the literature shows that investors are not fully able to unravel bias in analysts' forecasts (Hayes and Levine, 2000; Hilary and Hsu, 2013). Inherent uncertainty about the realization of future economic benefits associated with intangible assets together with high information asymmetry make it difficult for investors to understand the future implications of expenditure on intangible assets (i.e, E&E expenditure). Consequently, investors are likely to rely on analysts' forecasts to supplement company disclosures. On the one hand, Analysts' specialised knowledge is reflected in their forecasting and valuation models, enabling them to provide earnings forecasts that are likely to be more valuable to investors, meaning that investors can benefit from analysts' expertise when investing in firms with intangible assets of the complex nature. On the other hand, investors need be able to recognize the bias contained in these forecasts, because biased forecasts may lead them to mistake the prospects of the firms in this asset-specific industry.

This study focuses on the effect of the nature of a particular type of intangible assets, i.e., E&E expenditure, on analysts' strategic use of biases in their forecasts. The generalizability of the findings of this study to other types of intangible assets is not examined in this study. As different types of intangible assets exhibit different characteristics, future studies may investigate the factors associated with analysts' ability and behaviour to interpret intangibles-related information in other industries.

The literature identifies various analysts' incentives to bias their earnings forecasts: to curry favour with management, to generate underwriting business or trading commissions (Lin and McNicoles, 1998; Jackson, 2005), to analysts' cognitive limitations (Markov and Tamayo, 2006). This study considers that the access to management incentives motivates analysts strategically to bias their forecasts for information access from management because the uncertainty associated with the prospective outcomes of E&E activities engages analysts in the constant development of private information. Future research may investigate analysts' alternative incentives to the use of biases in their forecasts in relation to the nature and extent of the uncertainty associated with the firm' assets.

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Table 4.1
Descriptive Statistics

Variables	*Mean*	*Median*	*Std. Dev.*	*25%*	*75%*
$BIAS_{first}$	-0.044	-0.016	0.169	-0.059	0.006
$BIAS_{last}$	-0.017	-0.002	0.136	-0.020	0.006
$PESSBIAS_{last}$	0.418	0.000	0.494	0.000	1.000
PESSPTN	0.240	0.000	0.427	0.000	0.000
EXPL	0.076	0.033	0.108	0.010	0.097
SIZE	19.779	19.571	1.707	18.573	20.817
COVER	5.926	4.000	4.942	2.000	10.000
EARNCHANGE	0.116	0.031	0.317	0.012	0.075
LOSS	0.268	0.000	0.443	0.000	1.000
MB	2.835	2.035	2.817	1.291	3.332

Notes:
This table presents descriptive statistics for the sample of 794 firm-years across fiscal years 1993–2009. Because firm-years with the four possible patterns of analyst forecast bias are retained, the sample is smaller for *PESSPTN*, and consists of 705 firm-years. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. *BIAS* is the monthly signed forecast error for year *t*, measured as the difference between the firm's actual and forecasted annual earnings per share for year *t*, divided by share price in the first month following the prior year's earnings announcement. $BIAS_{first}$ is the *BIAS* calculated using the earliest forecast in fiscal year and $BIAS_{last}$ is the *BIAS* calculated using the latest forecast before the earnings announcement. $PESSBIAS_{last}$ is an indicator variable coded one if $BIAS_{last}$ is greater than or equal to zero, and zero otherwise. *PESSPTN* is an indicator variable equal to one if analysts exhibit a pessimistic-to-pessimistic pattern (that is, $BIAS_{first}$, the first forecast in fiscal year and $BIAS_{last}$, the last forecast in the final month before the earnings announcement are pessimistic, $BIAS_{first} \geq 0$ and $BIAS_{last} \geq 0$). *PESSPTN* is coded zero if analysts follow an optimistic-to-pessimistic pattern (that is, the first forecast in fiscal year is optimistic but the last forecast in the final month before the earnings announcement is pessimistic, $BIAS_{first} < 0$ and $BIAS_{last} \geq 0$), or if analysts follow an optimistic-to-optimistic pattern (that is, both the first and the last forecasts are optimistic, $BIAS_{first} < 0$ and $BIAS_{last} < 0$), or analysts follow a pessimistic-to-optimistic pattern (that is, analysts switch from initial pessimism to later optimism, $BIAS_{first} \geq 0$ and $BIAS_{last} < 0$). This variable is coded as missing for firm-years where the last forecast is the same as the first forecast. *EXPL* is the annual E&E expenditure (capitalized E&E expenditure plus E&E expense) for year *t*-1 divided by total assets at the end of year *t*-1 (total assets is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure). *SIZE* is logarithm of market value of equity at the end of year *t*-1. *COVER* is the number of analysts providing earnings forecasts for the firm for year *t*. *EARNCHANGE* is the absolute value of the difference between current year's actual earnings per share and last year's actual earnings per share, scaled by share price at the end of year *t*-1 (actual earnings per share is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure). *LOSS* is an indicator variable that equals one if the firm reports a loss for year *t* and zero otherwise. *MB* is the market-to-book ratio at the end of year *t*-1 (book value of equity is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure).

Table 4.2
Pearson Correlation Matrix

	$BIAS_{last}$	$PESSBIAS_{last}$	*PESSPTN*	*EXPL*	*SIZE*	*COVER*	*EARNCHANGE*	*LOSS*	*MB*
$BIAS_{last}$	1								
$PESSBIAS_{last}$	0.400***	1							
PESSPTN	0.315***	0.643***	1						
EXPL	0.054	-0.033	-0.033	1					
SIZE	0.112**	0.062	0.080*	-0.263***	1				
COVER	0.094*	0.102**	0.141***	-0.276***	0.684***	1			
EARNCHANGE	-0.221***	-0.067	-0.007	-0.013	-0.208***	-0.198***	1		
LOSS	-0.349***	-0.252***	-0.236***	0.309***	-0.289***	-0.353***	0.151***	1	
MB	0.013	-0.053	-0.075*	0.254***	0.136***	-0.060	-0.045	0.167***	1

Notes:
This table presents the Pearson correlation matrix for the sample of 794 firm-year observations across fiscal years 1993–2009. Because only firm-years with the four possible forms of analyst forecast bias are retained, the sample is smaller for *PESSPTN*, and consists of 705 firm-years. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. All variables are defined as in Table 4.1. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table 4.3
Regressions of analyst forecast bias on the exploration intensity and control variables

Panel A: OLS regression of analyst forecast bias on the exploration intensity

$$BIAS_{t,m} = \beta_0 + \beta_1 EXPL_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 COVER_t + \beta_4 EARNCHANGE_{t-1} + \beta_5 LOSS_t + \beta_6 MB_{t-1} + \beta_7 MONTH_t + \beta_8 YEAR_t + \varepsilon_t \quad (1)$$

Variable	*Coeff.*	*t-stat.*
Intercept	-0.178***	(-7.069)
EXPL	0.200***	(11.839)
SIZE	0.007***	(4.941)
COVER	-0.001**	(-2.218)
EARNCHANGE	-0.108***	(-16.505)
LOSS	-0.112***	(-29.543)
MB	0.000	(0.652)
MONTH	0.003***	(6.249)
YEAR	0.001***	(3.846)
Number of observations	7,016	
Adjusted R^2	18.8%	

Panel B: Logistic regression of the probability of analysts' issuing pessimistic forecasts on the exploration intensity

$$PESSBIAS_{t,m} = \beta_0 + \beta_1 EXPL_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 COVER_t + \beta_4 EARNCHANGE_{t-1} + \beta_5 LOSS_t + \beta_6 MB_{t-1} + \beta_7 MONTH_t + \beta_8 YEAR_t + \varepsilon_t \quad (2)$$

Variable	*Coeff.*	*z-stat.*
Intercept	-1.283***	(-2.837)
EXPL	1.493***	(4.545)
SIZE	0.018	(0.735)
COVER	0.010	(1.156)
EARNCHANGE	0.408***	(3.371)
LOSS	-1.560***	(-19.219)
MB	-0.044***	(-3.839)
MONTH	0.050***	(5.485)
YEAR	0.021***	(3.293)
Number of observations	7,016	
Pseudo-R^2	6.2%	

Notes:

Panel A of this table presents coefficient estimates and *t*-statistics (in parenthesis) from an OLS regression of analyst forecast bias on the exploration intensity and control variables, and panel B of this table presents coefficient estimates and *z*-statistics (in parenthesis) from a logistic regression of the probability of analysts' issuing pessimistic forecasts on the exploration intensity and control variables, for the sample of 7,016 monthly forecast observations across fiscal years 1993–2009. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. Clustering at the firm and year level or the firm level leads to the similar inference. The subscript t refers to year t, and the subscript m refers to month m. *BIAS* is the monthly signed forecast error for year t, measured as the difference between the firm's actual and forecasted annual earnings per share for year t, divided by share price in the first month following the prior year's earnings announcement. *PESSBIAS* is an indicator variable coded one if *BIAS* is greater than or equal to zero, and zero otherwise. *EXPL* is the annual E&E expenditure (capitalized E&E expenditure plus E&E expense) for year t-1 divided by total assets at the end of year t-1 (total assets is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure). *MONTH* is the number of months between the prior year's earnings announcement and the consensus forecast. For example, *MONTH* = 1 is the first month following the prior year's earnings announcement when a forecast is made, *MONTH* = 2 is the second month following the prior year's earnings announcement when a forecast is made, and so on. *YEAR* is the year trend in forecast bias, measured as the difference between the year of the forecast and the base year 1993 (the first year in the sample). All other variables are defined as in Table 4.1. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table 4.4
Logistic Regression of the probability of a pessimistic-to-pessimistic pattern exhibited in analysts' forecasts on the exploration intensity and control variables

$$PESSPTN_t = \beta_0 + \beta_1 EXPL_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 COVER_t + \beta_4 EARNCHANGE_{t-1} + \beta_5 LOSS_t + \beta_6 MB_{t-1} + \beta_7 YEAR_t + \varepsilon_t \quad (3)$$

Variable	*Coeff.*	*z-stat.*
Intercept	-0.477	(-0.304)
EXPL	2.329*	(1.891)
SIZE	-0.046	(-0.509)
COVER	0.055*	(1.853)
EARNCHANGE	0.441	(1.207)
LOSS	-1.999***	(-5.238)
MB	-0.057	(-1.268)
YEAR	0.012	(0.503)
Number of observations	705	
Pseudo-R^2	7.5%	

Notes:
This table presents coefficient estimates and *z*-statistics (in parenthesis) from a logistic regression of the probability of a pessimistic-to-pessimistic pattern exhibited in analysts' forecasts for firms with substantial E&E activities across fiscal years 1993–2009. Because only firm-years with the four possible patterns of analyst forecast bias are retained, the sample is smaller and consists of 705 firm-years. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. Clustering at the firm and year level or the firm level leads to the similar inference. The subscript *t* refers to year *t*. *PESSPTN* is an indicator variable equal to one if analysts exhibit a pessimistic-to-pessimistic pattern (that is, $BIAS_{first}$, the first forecast in fiscal year and $BIAS_{last}$, the last forecast in the final month before the earnings announcement are pessimistic, $BIAS_{first} \geq 0$ and $BIAS_{last} \geq 0$). *PESSPTN* is coded zero if analysts follow an optimistic-to-pessimistic pattern (that is, the first forecast in fiscal year is optimistic but the last forecast in the final month before the earnings announcement is pessimistic, $BIAS_{first} < 0$ and $BIAS_{last} \geq 0$), or if analysts follow an optimistic-to-optimistic pattern (that is, both the first and the last forecasts are optimistic, $BIAS_{first} < 0$ and $BIAS_{last} < 0$), or analysts follow a pessimistic-to-optimistic pattern (that is, analysts switch from initial pessimism to later optimism, $BIAS_{first} \geq 0$ and $BIAS_{last} < 0$). This variable is coded as missing for firm-years where the last forecast is the same as the first forecast. *EXPL* is the annual E&E expenditure (capitalized E&E expenditure plus E&E expense) for year *t*-1 divided by total assets at the end of year *t*-1 (total assets is re-stated on an "as-if-expensing" basis for firms that capitalize E&E expenditure). *YEAR* is the year trend in forecast bias, measured as the difference between the year of the forecast and the base year 1993 (the first year in the sample). All other variables are defined as in Table 4.1. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

Table 4.5
Regressions of analyst forecast bias on the exploration intensity and control variables conditional on firms' operating activities

Panel A: OLS regression of analyst forecast bias on the exploration intensity conditional on firms' operating activities

$$BIAS_{t,m} = \beta_0 + \beta_1 EXPL_{t-1} \times LRev\_HExpl_{t-1} + \beta_2 EXPL_{t-1} \times HRev\_HExpl_{t-1} + \beta_3 EXPL_{t-1} \times LRev\_LExpl_{t-1} + \beta_4 EXPL_{t-1} \times HRev\_LExpl_{t-1} + \beta_5 SIZE_{t-1} + \beta_6 COVER_{t-1} + \beta_7 EARNCHANGE_{t-1} + \beta_8 LOSS_t + \beta_9 MB_{t-1} + \beta_{10} MONTH_t + \beta_{11} YEAR_t + \varepsilon_t \quad (4)$$

Variable	*Coeff.*	*t-stat.*
Intercept	-0.176***	(-6.944)
EXPL × LRev_HExpl	0.202***	(10.689)
EXPL × HRev_HExpl	0.168***	(4.284)
EXPL × LRev_LExpl	0.176	(0.705)
EXPL × HRev_LExpl	-0.083	(-0.385)
SIZE	0.007***	(4.872)
COVER	-0.001*	(-1.680)
EARNCHANGE	-0.109***	(-16.555)
LOSS	-0.112***	(-29.388)
MB	0.000	(0.480)
MONTH	0.003***	(6.223)
YEAR	0.001***	(4.014)
Number of observations	7,016	
Adjusted R^2	18.7%	

Table 4.5 – Continued

Panel B: Logistic regression of the probability of analysts' issuing pessimistic forecasts on the exploration intensity conditional on firms' operating activities

$$PESSBIAS_{t,m} = \beta_0 + \beta_1 EXPL_{t-1} \times LRev\_HExpl_{t-1} + \beta_2 EXPL_{t-1} \times HRev\_HExpl_{t-1} + \beta_3 EXPL_{t-1} \times LRev\_LExpl_{t-1} + \beta_4 EXPL_{t-1} \times HRev\_LExpl_{t-1} + \beta_5 SIZE_{t-1} + \beta_6 COVER_{t-1} + \beta_7 EARNCHANGE_{t-1} + \beta_8 LOSS_t + \beta_9 MB_{t-1} + \beta_{10} MONTH_t + \beta_{11} YEAR_t + \varepsilon_t \quad (5)$$

Variable	*Coeff.*	*z-stat.*
Intercept	-1.193***	(-2.620)
EXPL × LRev_HExpl	1.456***	(3.979)
EXPL × HRev_HExpl	1.437**	(1.992)
EXPL × LRev_LExpl	-6.415	(-1.343)
EXPL × HRev_LExpl	3.601	(0.950)
SIZE	0.016	(0.629)
COVER	0.006	(0.719)
EARNCHANGE	0.399***	(3.289)
LOSS	-1.550***	(-19.066)
MB	-0.043***	(-3.707)
MONTH	0.050***	(5.508)
YEAR	0.020***	(3.028)
Number of observations	7,016	
Pseudo-R^2	6.3%	

Notes:

Panel A of this table presents coefficient estimates and *t*-statistics (in parenthesis) from an OLS regression of analyst forecast bias on the exploration intensity and control variables conditional on firms' operating activities, and panel B of this table presents coefficient estimates and *z*-statistics (in parenthesis) from a logistic regression of the probability of analysts' issuing pessimistic forecasts on the exploration intensity and control variables conditional on firms' operating activities, for the final sample of 7,106 monthly forecast observations across fiscal years 1993–2009. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers. Clustering at the firm and year level or the firm level leads to the similar inference. The subscript *t* refers to year *t*, and the subscript *m* refers to month *m*. *BIAS* is the monthly signed forecast error for year *t*, measured as the difference between the firm's actual and forecasted annual earnings per share for year *t*, divided by share price in the first month following the prior year's earnings announcement. *PESSBIAS* is an indicator variable coded one if *BIAS* is greater than or equal to zero, and zero otherwise. *LRev_HExpl* is an indicator variable that equals one if a firm-year observation is from the *LRev_HExpl* group. *HRev_HExpl*, *LRev_LExpl* and *HRev_LExpl* are indicator variables indicating firm-year observations from the *HRev_HExpl*, *LRev_LExpl* and *HRev_LExpl* groups. I partition sample firms into four groups based on the median values of their annual operating revenue *REV* ($108.916 million) and *EXPL* measure (0.033), where High is above or equal the median and Low is below the median: (1) Low *REV* and High *EXPL* group (*LRev_HExpl*); (2) High *REV* and High *EXPL* group (*HRev_HExpl*); (3) Low *REV* and Low *EXPL* group (*LRev_LExpl*); and (4) High *REV* and Low *EXPL* group (*HRev_LExpl*). All other variables are defined as in Table 4.1. ***, **, * indicate significance at 1%, 5%, and 10% levels in a two-tailed test, respectively.

5 CHAPTER FIVE

CONCLUSIONS

5.1 Introduction

Motivated by the distinctiveness of the Australian setting with continuous disclosure to the stock market, and the prominence of the resources sector in the Australian economy, this thesis has examined the properties of analysts' forecasts in Australia. Specifically, the first paper (in Chapter Two) identified the superior forecast measure in Australia. Using the extractive industry as a special setting, the second paper (in Chapter Three) evaluated the role of analysts in reducing the high information asymmetry exhibited in this industry. The third paper in (Chapter Four) examined bias in analysts' forecasts in the extractive industry where biased forecasts may affect investors' decisions to a greater extent because of the nature and extent of the uncertainty associated with exploration and evaluation (E&E) expenditure.

The remainder of this chapter is organized as follows. Section 5.2 presents summaries and findings of each of the three papers comprising the thesis. Section 5.3 discusses the contributions and implications overall. The limitations of the thesis and suggestions for future research are provided in Section 5.4.

5.2 Summaries and Findings

5.2.1 Paper 1: Australian Evidence on the Accuracy of Analysts' Expectations: The Value of Consensus and Timeliness Prior to the Earnings Announcement

Paper 1 provided evidence of the accuracy of alternative forecast measures and the importance of diversifying idiosyncratic individual error across analyst forecasts in the consensus forecast. Using a sample of 4,358 firm-year observations of annual Australian analyst forecasts for the period from fiscal 1987 to fiscal 2007, Paper 1 compared the relative accuracy of the consensus forecast against the most recent forecast prior to the earnings announcement. It examined whether the number of analysts following a company or the timeliness of an individual analyst's forecast is more strongly associated with the superior forecast measure. The results indicate that, whilst in the late 1980s there is some evidence that the most recent forecast is more accurate than the consensus, since the early 1990s the accuracy of the consensus forecast has consistently outperformed the most recent forecast. The consensus forecast is more accurate in 15 out of 17 more recent years, and the differences are significant for nine out of those 15 years. The forecasting superiority of the consensus forecast is attributed to the aggregation value of the consensus outweighing the small timing advantage of the most recent forecast over the short forecast horizon examined in this study.

5.2.2 Paper 2: Exploration Intensity, Analysts' Private Information Development and Their Forecast Performance

Paper 2 examined the relations between the intensity of E&E activities and analysts' private information development activities and forecast accuracy. The paper also investigated factors associated with analysts' reliance on private information in environments with substantial uncertainties surrounding E&E activities. The OLS pooled cross-sectional regressions were estimated on a sample of 781 firm-years representing the ASX-listed extractive companies with reported E&E activities and analyst following between the fiscal years 1993 and 2009. The Barron et al. (1998)

analyst consensus construct was used to capture the average proportion of private information conveyed in analysts' forecasts.

The study found that the proportion of private information contained in analysts' forecasts increases with the intensity of E&E activities, consistent with analysts developing relatively more private information in response to greater intensity of E&E activities. The study also found that the accuracy of analysts' average forecasts increases with the intensity of E&E activities even after controlling for the number of forecasts and individual analyst forecast errors. This suggests that the improved accuracy in analysts' forecasts is at least partially associated with analysts' increased efforts in private information development. Additional analysis revealed that the effect of exploration intensity on the analysts' information environment is more pronounced for firms with substantial E&E activities but limited production activities, and that analysts' private information development activities are mainly related to the capitalized E&E expenditure.

5.2.3 Paper 3: Exploration Intensity and Analyst Forecast Bias

Using a sample of 7,016 monthly forecast observations representing the ASX-listed extractive companies with reported E&E activities and analyst coverage across fiscal years 1993–2009, Paper 3 examined the effect of the nature of the firms' assets on analysts' strategic use of biases. The paper also investigated the form of the forecast bias analysts use to curry favour with managers for firms with high exploration intensity. The OLS pooled cross-sectional regression was used to test for a relationship between the intensity of E&E activities and analyst forecast bias, and the logistic cross-sectional regression was used to test for the probability of analysts following a pessimistic-to-pessimistic pattern in their forecasts for firms with substantial E&E activities.

The study found that pessimism in analysts' forecasts increases with the intensity of E&E activities, indicating that the effect of analysts biasing their forecasts to gain information access from managers is more pronounced for firms with higher levels of E&E expenditure. The results also suggest that analysts are more likely to follow a pessimistic-to-pessimistic pattern in response to greater exploration intensity, consistent with analysts' strategic use of the pessimistic biases to improve access to managerial information and their forecast error consistency. Paper 3 further investigated the effect of exploration intensity on analysts' forecast biases conditional on firms' operating activities. It found that the effect of analysts issuing biased forecasts to please managers is increasing for firms that heavily engage in E&E activities relative to production activities. For these firms, their future prospects largely depend on the overall economic potential of exploration projects. Analysts strive to develop private information to be able to better incorporate and account for the high level of uncertainty surrounding these firms' E&E activities. Since managers are in a position to help analysts form accurate expectations of future earnings realizations (Ke and Yu, 2006), analysts are likely to accommodate managers' demand so as to curry favour.

5.3 Contributions and Implications

The thesis makes several contributions to the academic literature on analysts' forecasts, intangible assets and extractive industries. The findings of this thesis have several implications for investors and other parties using analysts' forecasts.

The first is with respect to the contributions to the literature on analysts' forecasts. Paper 1 demonstrated that the consensus forecast is a superior measure of the market's earnings expectations in Australia, and that the greater accuracy of the consensus forecast comes from diversifying away idiosyncratic error in individual analyst forecasts. The contribution of Paper 1 is, therefore, that it provides insights into the extent to which the expected level of forecast accuracy is realised, and reasons for the greater accuracy in the superior forecast measure, in a non-U.S. market with a distinct disclosure regime and different industry composition. The findings of Paper 1 also support the market practitioners' views as evidenced by press reports, that the consensus forecast is a better measure of the market's expectations. An implication of these findings is that the consensus forecast should be most useful to investors in forming expectations for future earnings.

Paper 2 revealed that analysts develop more private information for firms with greater exploration intensity. Although idiosyncratic errors in the individual analyst forecasts increase with private information search activities, these idiosyncratic errors can be averaged out through the aggregation process associated with the calculation of the consensus forecast. This implies that the consensus forecast is useful to investors in forming expectations about future performance of extractive firms.

The thesis also contributes to the literature on intangible assets. Prior research has shown that the degree of uncertainty is greater for investments in intangible assets than other types of capital investments (Kothari et al., 2002), and that analysts expend more resources and efforts in developing private information for firms with higher levels of intangible assets (Barth et al., 2001; Barron et al., 2002). Paper 2 suggests that for intangible assets with a limited scope of diversity and innovativeness, such as E&E projects, analysts are able to realise the benefits of their specialised knowledge, private information development and superior financial modelling skills to evaluate the future prospects of firms in carrying out projects at the various stages of exploration and development. Analysts are able to provide more accurate forecasts.

Paper 3 provides evidence on whether the nature and extent of the uncertainty associated with firms' intangible assets is related to analysts' strategic use of biases to please management so as to gain better information access. The results of this study show that the analysts' forecast bias increases with the extent of E&E activities, consistent with analysts trading off biases to gain information access for firms with inherent uncertainty about the realization of future economic benefits associated with intangible assets. The results have several implications for investors:

The inherent uncertainty together with high information asymmetry make it difficult for investors to understand the future implications of expenditure on intangible assets (i.e., E&E expenditure). Consequently, investors are likely to rely on analysts' forecasts to supplement company disclosures. On the one hand, analysts' specialised knowledge is reflected in their forecasting and valuation models, enabling them to provide earnings forecasts that are likely to be more valuable to investors, meaning that investors can benefit from analysts' expertise when investing in firms with intangible assets of the complex nature. On the other hand, investors need be able to recognize the bias contained in analysts' forecasts in this context, because biased forecasts may lead them to mistake the prospects of the firms in this asset-specific industry.

With respect to the contributions to the literature on extractive industries, the findings of Paper 2 imply that market participants can benefit from analysts' expertise in developing private information and can use analysts' forecasts to expand their (market participants') information set when investing in extractive companies with high exploration intensity. Paper 2 also contributes to the literature by shedding light on the effectiveness of accounting disclosure for E&E expenditure. Prior literature suggests that, compared with the full cost accounting method, an important advantage of other accounting methods such as the successful efforts and area of interest is that separating successful from unsuccessful investments may provide relevant information to investors (Naggar, 1978; Harris and Ohlson, 1987). Paper 2 provides some evidence of this advantage by showing that analysts' private information development activities are mainly related to capitalized E&E expenditure. It suggests that analysts may perceive expensed E&E costs from unsuccessful exploration projects to be irrelevant information. Finally, Paper 3 contributes to the literature on extractive industries by providing evidence that the inherent uncertainty associated with the payoffs to E&E expenditure is related to analysts' strategic behaviour in the extractive industries.

5.4 Limitations and Suggestions for Future Research

Several limitations of this research need to be recognised. The first is with respect to the firm-year observations in Papers 2 and 3. Of more than 3,000 firm-years of the ASX-listed extractive companies reporting E&E expenditure in annual reports, or for which E&E expenditure can be estimated using other financial statement line items for the period between the fiscal years 1993 and 2009, only about 800 firm-years have analyst forecasts of one-year ahead annual earnings available in the I/B/E/S database. This substantial reduction in sample size is due to the fact that many listed junior exploration companies with no product sales do not attract analyst following. Notwithstanding that junior exploration companies play a critical role in investing in exploration projects to find new assets (PricewaterhouseCoopers, 2013), many of them with no product sales are not included in the sample of this research.

Moreover, this thesis focuses on the effect of the nature of a particular type of intangible asset, i.e., E&E expenditure, on the analysts' information environment and their strategic behaviour. The generalizability of the findings of this study to other types of intangible assets is not examined in this thesis.

Future studies may expand this current research to other types of intangible assets in order to validate or qualify the effect of the nature and extent of the uncertainty associated with intangible assets on the analysts' information environment and their strategic behaviour in a broader context. As different types of intangible assets in other industries may exhibit different characteristics, future studies may investigate other factors associated with analysts' ability and behaviour around the interpretation of intangibles-related information.

Finally, several possible research directions relating to each of the three papers comprising the thesis are discussed below. Paper 1 provides evidence that the consensus forecast is a superior measure of the market' earnings expectations. Future research may profitably consider whether consensus forecasts can be improved by forming a consensus based on the forecasts of a subset of highly skilled analysts or analysts possessing other, particular attributes.

Paper 2 examined the effect of capitalization of E&E expenditure using the area of interest accounting method on analysts' private information development activities and forecast performance. The area of interest refers to an individual geological area whereby the presence of a mineral deposit or an oil or natural gas field is considered favourable or has been proven to exist, and extractive companies are required to adopt this method to account for E&E expenditure in Australia (AASB, 2004). Currently under IFRS 6 *Exploration for and Evaluation of Mineral Resources*, which became effective in 2006 and specifically addresses extractive activities, extractive companies have accounted for E&E costs in a variety of ways, including the successful efforts, full cost and area of interest accounting methods. Prior literature demonstrates different levels of value relevance using the successful efforts and full costs accounting methods in the extractive industries (Bryant, 2003). Future studies may extend this line of research to examine the impact of different accounting methods to account for E&E costs on the analysts' information environment.

Paper 3 considers that the incentive to gain access to management motivates analysts to strategically bias their forecasts because the uncertainty associated with the prospective outcomes of E&E activities engages analysts in a constant development for private information. The literature identifies various analysts' incentives to bias their earnings forecasts: to curry favour with management, to generate underwriting business or trading commissions (Lin and McNicoles, 1998; Jackson, 2005), or because of analysts' cognitive limitations (Markov and Tamayo, 2006). Future research may investigate alternative analysts' incentives to bias their forecasts in relation to the nature and extent of the uncertainty associated with the firm' assets.

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