Accounting Standard Complexity, Analyst Forecast Properties, and Auditor Industry Specialization

Abstract

This paper examines the impact of international accounting standards (hereafter IFRS) complexity on analyst forecast properties including forecast errors, forecast dispersion, and forecast revision. Because Industry Specialisation (ISP) is likely to moderate the effect of complexity, it is introduced as a moderating variable in this analysis. The complexity of individual IFRS standards is measured based on IFRS reconciliation statements capturing the adjustments on accounts affected by the changes in accounting standards. We analyze 322 companies listed on the Australian Securities Exchange (ASX). Our results suggest that all IFRS standards are not equally complex. A few standards are relatively more complex. These standards have a positive effect on analyst forecast errors, forecast dispersion, and forecast revision. In addition, we find that city-level industry specialist auditors (ISP) can mitigate the adverse impact of IFRS complexity on analyst forecast errors but not on forecast dispersion and revision. More interestingly, the mitigating effect of industry specialists is restricted to only a group of companies exposed to a higher level of aggregate IFRS complexity. The findings of our study contribute to the IFRS literature by identifying the most complex accounting standards. Secondly, this study provides an ex-ante experiment of IFRS adoption which can be used by the adopting countries to understand the impact of IFRS on the analyst forecasts. Finally, our study helps regulators to understand the effects of the complexity of accounting standards on users of financial statements.

Keywords: IFRS; complexity; financial analyst forecast; auditor industry specialization

1. Introduction

This study investigates the impact of accounting complexity arising from IFRS adoption on analyst forecast properties including forecast errors, dispersion, and revision. We conjecture that analysts' forecasting abilities are adversely affected by more complex accounting standards. In addition, we investigate whether high-quality audit, proxied by auditor industry specialization, moderates the relation between accounting complexity and analyst forecast properties.

Prior research on the impact of IFRS adoption on analyst forecasting properties either investigates the impact of IFRS using a dummy variable to differentiate post-IFRS period from the pre-IFRS (e.g., Tan et al., 2011; Xi and Yang., 2016) or tests the impact of the difference in clauses between local standards and IFRS on forecast properties of analyst forecast performance (Byard et al., 2011; Bae et al., 2008). The findings on the effect of IFRS on analysts are largely inconclusive. Three studies investigate the impact of specific standards on analysts' forecast properties (Bugeja et al., 2015, Cotter et al., 2012, Matolcsy and Wyatt, 2006), but all limit their focus on standards pertinent to intangibles or operating segments. Later, Ahmed et al. (2013) conduct a meta-analysis of IFRS adoption effects on earnings transparency, capital market and quality of analysts 'earnings forecasts. They document that analysts' forecast accuracy has increased in post-IFRS adoption. Our study differs from the extant studies in that we focus on the complexity of IFRS measured at both an aggregate level and for individual standards. This allows identification of collective effects of complex standards and the effects of individual standards on analyst forecasting abilities.

Specifically, this study uses the concept of accounting complexity to capture the challenge that analysts face as a result of changing accounting standards.[1] We calculate complexity scores for a set of complex IFRS standards based on financial statements reconciliation, which is prepared during the first year of IFRS adoption by companies in Australia. The data required to compute complexity are hand-collected from annual reports. Measuring complexity scores for each accounting standard separately enables us to discern

[1] The extant accounting literature measures complexity as readability using a technique of syntax analysis (for example see, Filzen and Peterson, 2015, Lehavy et al., 2011), the length of the reports by word counts (for e.g., Franco et al., 2015). In our study, we measure complexity based on individual standards.

how the complexity of standards affects analyst forecast properties by those standards individually.

This study exploits the unique setting of Australia to examine the effects of the complexity of accounting standards. In 2005, Australia adopted all accounting standards which were issued by the International Accounting Standards Board (IASB). So, it is worthwhile to check how such a big change in the accounting reporting environment affected the accounting information users such as financial analysts. Australia has a mature financial analyst industry where analysts are expected to have reasonable financial literacy and use their financial skills to analyze annual report information.

Using 322 sample firm observations from the IFRS adoption year, our empirical analyses show that complexity at an aggregate level does not explain the increase in forecast error, dispersion, and revision. Analyses using complexity scores of the set of individual standards show that analyst forecast errors are positively associated with accounting complexity arising from two standards, namely AASB 2 *Share-based Payment* and AASB 132 *Financial Instruments: Presentation*. AASB 117 *Leases* is positively associated with forecast dispersion and forecast revision increases with the increase in accounting complexity of two standards, AASB 3 *Business Combination,* and AASB 117 *Leases.* Our examination on the moderating effect of high-quality audit on the relation between accounting complexity and forecast properties is conducted with high vs. low complexity subsamples. The results show that analyst forecast error is lower in firms audited by city-level ISP compared to those audited by non-ISP.[2]

This study contributes to IFRS and analyst forecast literature in several ways. First, our analysis using individual standards identify a few specific standards as more complex than others resulting in impaired analyst forecast performance. Additionally, this study shows the moderating effect of high-quality audit on the relation between accounting complexity and forecast properties, pinpointing the importance of auditor's monitoring effect when firms face changes in accounting standards. Although prior studies demonstrate that high-quality auditors can reduce analyst forecast errors and forecast dispersion (Behn et al., 2008), our study

[2] However, we do not find any evidence on the moderating effect of national-level industry specialization (*NATIONAL_ISP)* on the association between forecast properties and aggregate accounting complexity in either original six or new-six category of accounting standards.

advances their findings by showing that this effect of high-quality auditors on analyst forecast performance is more pronounced in a context where firms face accounting complexity.

The paper is organized as follows. Section 2 reviews the literature and develops our hypotheses. Empirical procedure and sample selection are described in Sections 3. Section 4 reports the analysis of the impact of accounting complexity on analyst forecast properties. Section 5 discusses the moderating effect of high-quality audit on the relation between accounting complexity and forecast errors. Section 6 concludes.

2 Literature Review and Hypothesis Development

2.1 Accounting Complexity and Analyst Forecasting Error

Financial analysts are the most important, sophisticated, and visible users of financial statements (Bae et al., 2008, Schipper, 1991, Tan et al., 2011). They provide earnings forecasts, buy/sell recommendations and other information to brokers, money managers and institutional investors (Lang and Lundholm, 1996). The extant IFRS and financial analyst forecast studies can be broadly classified into two streams including (i) voluntary adoption of IFRS studies and analyst forecast properties (Ashbaugh and Pincus, 2001, Bae et al., 2008, Ernstberger et al., 2008, Hodgdon et al., 2008); and (ii) mandatory adoption of IFRS and analyst forecast properties (Byard et al., 2011; Jiao et al., 2012; Tan et al., 2011; Xi and Yang, 2016). All voluntary IFRS adoption and analyst forecast studies provide consistent results that the analysts' consensus forecast accuracy significantly improves after firms adopting IFRS voluntarily. However, studies of mandatory adoption of IFRS provide inconclusive results, and, therefore, provide the motivation to explore this phenomenon further. For instance, Horton et al. (2013), investigate whether improved analyst forecast accuracy can be attributed to (i) higher-quality information; (ii) greater comparability, or (iii) constraining managers' opportunities to manipulate earnings. Based on a large sample covering all available companies of all countries in The Institutional Brokers' Estimate System (*I/B/E/S)*, they find that forecast accuracy increases due to both higher information quality and greater comparability of information prepared on the basis of IFRS.

Tan et al. (2011) argue that if widespread mandatory IFRS adoption increases timeliness, analyst following may also increase because of the increasing usefulness of accounting data. However, due to increasing earnings volatility, forecast accuracy may decrease. Alternatively, the subjectivity involved in the fair value approach under IFRS may result in earnings smoothing. This, in turn, may cause the analyst following to decrease because of the decreasing usefulness of accounting information, and forecast errors may also decrease.

On the other hand, Byard et al. (2011) contend that mandatory adopters may not provide enough incentive for analysts to follow IFRS rigorously because firms may have already optimized their financial reporting quality under the local standards, resulting in little change in the analyst information environment. By examining 1168 EU IFRS mandatory adopter firms and 250 voluntarily IFRS adopter firms, they find that simply making IFRS mandatory, on average, does not change the analysts' information environment (forecast errors and forecast dispersion), but significantly improves the information environment for firms domiciled in countries with both strong enforcement regimes and significant differences between domestic accounting standards and IFRS.[3]

Focusing on a single country, Cotter et al. (2012) examine the impact of IFRS disclosure on analyst forecasts of 145 Australian listed firms from 2003 to 2007. They document that analyst forecast accuracy improves in both the adoption year and post-adoption years but dispersion does not decrease. They claim that improvement in forecast accuracy and unchanged dispersion can be attributed to additional efforts and attention which was given to IFRS during the adoption period. In the same setting, Chalmers et al. (2012) investigate the association between analyst forecast accuracy and dispersion and the new methods of intangible reporting under IFRS. They find that the association between intangibles and analyst forecast error is reduced after the adoption of IFRS. IFRS no longer permits a firm's straight-line amortization of intangible assets, instead prescribes a new impairment approach, thus decreasing the forecast errors.

Taken together, it is evident that none of the prior studies comprehensively explores the impact of changes in individual IFRS standards on analyst forecasting properties, although Chalmers et al. (2012) make an important contribution with regard to intangibles. Our study seeks to extend this line of investigation, by investigating the impact of each of the IFRS standards that have been identified as 'complex'.

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[3] Byard et al. (2011) examine the effect of mandatory adoption of IFRS on financial analysts' information environment in 1168 EU IFRS adopter firms and 250 non-adopting control firms (voluntarily IFRS adopter firms).

Analyst forecast literature reaches consensus that analyst forecast properties are affected by (i) analysts' abilities and analyst expertise (Ramnath et al., 2008); (ii) reporting complexity (Chang et al., 2016; Plumlee, 2003); and (iii) economic complexity (Chang et al., 2016). Chang et al. (2016) investigate the impact of complexity due to ambiguous and unclear standards regarding derivatives on analyst forecast properties. They categorized their entire sample into different groups to disentangle reporting complexity from economic complexity.[4] Through empirical analysis, they find that reporting complexity, rather than economic complexity, is significantly associated with analyst forecast errors. Plumlee (2003) investigates and finds that reporting complexities arising from changes in tax laws are significantly associated with forecast errors.[5]

Following this line of reasoning, our study investigates if analyst forecast errors increase because of increased reporting complexity arising from IFRS adoption. We posit that if certain IFRS standards are complex evidenced by the higher/significant levels of differences between domestic GAAP and IFRS standards, an analyst may not be able to analyze IFRS based financial statements or make forecast decisions without required sufficient information, thereby results in less accurate forecasts. We develop our first hypothesis as follows:

H1: Accounting complexity arising from IFRS is negatively associated with analyst forecast accuracy.

2.2 Accounting Complexity and Analyst forecast dispersion

Forecast dispersion (hereafter *DISP*), a measure of uncertainty embedded in earnings, is one of the important analyst forecast properties. It is perceived by investors to be valuable information because it indicates the uncertainty of future performance (Givoly and Lakonishok, 1984). It is argued that better disclosures reduce information asymmetry (Brown and Hillegeist,

[4] Because prior literature show that first derivative accounting standards such as Statement of Financial Accounting Standards (SFAS) No 133/138 [from 2000-2003] were neither able to clear about the conditions of derivatives contracts, nor, comparability issues of different contracts (Pollock, 2005). However, SFAS 149 and later standards repair the problems of SFAS 138/139. However, investigation of the impact of economic complexity is beyond the scope of our study. Moreover, discriminating reporting complexity from economic complexity is challenging, if not impossible (Chang et al., 2016)). In addition, as economic factors are considered when accounting standards are issued (Peterson, 2012). Our study is based on only reporting complexity reflected in IFRS-AGAAP reconciliation statements, related to IFRS adoption.

[5] Two changes are regarding tax rates; one change is for calculation of taxable income and three changes are related to tax credits. Plumlee (2003) uses analyst effective tax rate (ETR) forecast as the dependent variable in her study.

2003a), and consequently improve analyst forecast consensus (Byard and Shaw, 2003). Empirically, Lang and Lundholm (1996) provide evidence of lower dispersion among individual analysts due to informative disclosures.

However, IFRS forecast dispersion studies provide mixed results. For instance, on the one hand, it is argued that due to inexperience, analysts may face difficulty in understanding and interpreting information presented under a set of accounting standards that differ from their domestic GAAP. This may result in heterogeneity in earnings forecasts (Cuijpers and Buijink, 2005). Cuijpers and Buijink (2005) investigate the impact of voluntary adoption of IAS or US GAAP on information asymmetry for 133 non-financial firms in the EU. They find that forecast dispersion among individual analysts increases for firms adopting IAS or US GAAP. However, they document an increase in analyst following for firms adopting IAS or US GAAP compared to non-adopting firms. However, Cotter et al. (2012) examine financial analyst forecasting properties of 145 Australian listed firms for the period 2003–2007 and find that forecast dispersion remains unchanged in the IFRS adoption year.

Nevertheless, prior research shows that forecast dispersion may also decrease with the adoption of IFRS, because of improvement in information environment through enhanced disclosures required under IFRS and increasing comparability of financial reports (e.g., Bae et al., 2008; Horton et al., 2013). Studying a sample of 1,168 mandatory IFRS adopters from twenty European countries, Byard et al. (2011) find that analysts' absolute forecast dispersion decreases upon mandatory adoption of IFRS. However, they limit their findings to those that countries have both strong enforcement and significant differences between Domestic Accounting Standards (DAS) and IFRS. For instance, though mentioned in earlier hypothesis development, Chalmers et al. (2012) investigate the impact of IFRS on forecast properties taking a sample of 3,328 observations in Australia covering pre- and post-IFRS adoption periods. Similarly, they find that the impairment approach suggested by IFRS provides more information compared to the former straight-line amortization approach under local standards (i.e., Australian Generally Accepted Accounting Principles, known as AGAAP), thereby decreasing forecast dispersion.

Unlike the extant IFRS and analyst forecast studies, we hypothesize that due to accounting complexity arising from IFRS especially in the first year of adoption, the learning curve of analysts would be steeper and some analysts are likely able to learn the IFRS effect more efficiently than others. This expectation leads to the development of the following directional hypothesis:

H2: Accounting complexity arising from IFRS is positively associated with analyst forecast dispersion.

2.3 Accounting Complexity and Forecast Revision

Analyst forecast revision has important implications for investors who revise their beliefs of earnings based on analyst forecast revision (Mendenhall, 1991) because investors by themselves are unable to determine the persistence of earnings when earnings are announced (Freeman and Tse, 1989). Following the approach of Barth and Hutton (2004), we measure forecast revision at consensus level as the difference between the last mean forecast made before current year earnings announcement date and the first mean forecast made after last year earnings announcement date.

Prior studies find that forecast revision can predict a firm's future profitability. For instance, Barth and Hutton (2004), in comparing hedge return to different strategies, investigate whether forecast revision can reveal information about earnings persistence beyond that obtained from accruals. Barth and Hutton (2004) document that a combined strategy of accruals and forecast revision can generate a return significantly larger than either of the two individual strategies. Clement and Tse (2003) investigate whether investors can extract the required information from analysts' characteristics which are associated with forecast accuracy. In particular, they find that investor's response to forecast revisions are influenced by other forecast characteristics such as timely forecasts, broker firms' size, and frequency of the forecasts other than forecast accuracy. They concluded that investors' response to forecast revision indicates that the forecast accuracy is not all that matters.

Prior research has been identified that attempts to investigate the impact of IFRS adoption on the tendency of analyst forecast revision. We posit that analysts revise their forecast in response to change in accounting standards from local GAAP to IFRS on the following grounds. First, it takes time for analysts to adjust their earnings predictions based on new accounting standards. This may be due to analysts' lack of experience in comprehending and interpreting accounting-related regulations. Plumlee (2003) predicts and finds that complexity arising from changes in tax laws affects analyst forecast errors and forecast revisions, suggesting that analysts do not consider complex information in forecast revision as this information does not accurately support them in forecasting firms' effective tax rates (ETR). Second, analysts' previous knowledge of AGAAP and firms' historical accounting information forms the basis of their forecasts for contemporaneous and future performance.

During the year of IFRS adoption, analysts' early forecasts are firstly formed on the basis of their understanding of historical information. However, they may gradually realize the deviations of their predictions from the actual performance that is prepared using IFRS and thus make forecast revisions. This realization may occur through their newly acquired knowledge of IFRS, management guidance, and most importantly, firms' disclosures of quarterly financial results. The reconciliation adjustments in the first year of IFRS adoption are used to proxy for the differences in accounting treatments. The greater they are, the more likely analysts are to conduct forecast revisions in the year of adoption. Taken together, our study predicts a positive relationship between accounting complexity and forecast revision and develops the following directional hypothesis:

H3: Accounting complexity arising from IFRS is positively associated with analyst forecast revision.

2.4 Accounting complexity, audit quality, and financial analyst forecast properties

We also examine the moderating role of audit quality on the relationship between accounting standard complexity and financial analyst forecast properties. It is argued that analyst forecasts properties are also moderated by audit quality because financial information is used by analysts as one of the primary resources for stock analysis and earnings forecast. The high quality auditor provides assurance to accounting information quality (Stokes and Webster, 2010), and thus analysts' forecast performance should be improved when they use high quality accounting information assured by a quality auditor (e.g., Behn et al., 2008). Following this line of argument, a stream of literature examines and finds supportive evidence of the discernible effect of audit quality on the properties of analysts' forecasts (Behn et al., 2008; Payne, 2008; Yi and Wilson, 2016; He et al., 2014). Behn et al. (2008) find that there is a positive association between high quality and analyst forecast accuracy. More specifically, they show that forecast accuracy is higher and dispersion is lower for firms audited by industry specialist audit firms.

He et al. (2014) extend Behn et al. (2008) to test the impact of high quality audits on the information environment in which analysts operate. They find that higher audit quality results in analysts placing more weight on public rather than private information. In addition, both analysts' common and private information tends to be more precise for the companies audited by industry specialists. Yi and Wilson (2016) argue and find that analyst forecast error is lower for the firms audited by industry specialists if the firm is given less coverage by industry specialized analysts. This finding suggests a complementary effect of high quality auditors in reducing analyst forecast errors, especially when analysts are less sophisticated.[6]

Given the theoretical argument on the importance of high quality auditor and the aforementioned empirical evidence, the main motivation is to examine whether high quality auditors improve analyst forecast performance when analysts face greater reporting uncertainty and difficulty due to changing accounting standards. We use industry specialization of auditor following the approach of Krishnan et al. (2013), as a proxy for high quality auditor.[7] Industry specialist auditors have more experience and training than non-specialist auditor (Sun and Liu, 2011), and they are familiar with accounting principles, specific industries', and specific firms' transaction processes and therefore can make more effective professional judgments and be more likely to detect accounting fraud (Tang and Peng, 2013). We argue that the adverse effects of accounting standard complexity on analyst forecast performance can be ameliorated if the firms are audited by ISP auditors as ISP auditors are distinguished because of their differentiated audit quality. The following hypothesis is formulated:

H4: The negative impact of IFRS complexity on analyst forecast properties is moderated by high quality audits**.**

3 Empirical Procedures

3.1 Measurement of Variables

3.1.1 Measurement of Dependent variables

The dependent variables, in our study, are analyst forecast properties including analyst forecast error (*AFE*), dispersion (*DISP*), and revision (*REVISION*). *AFE* is measured as the absolute value of analyst forecast error that is, the median forecast minus actual EPS and then is deflated by the stock price at the end of last year.

[6] Conversely, Payne (2008) shows that analysts' forecast errors are greater for the firms audited by an industry specialist. They argue that this is due to focus on end-of-year forecasts which induce benchmark-beating incentives for earnings manipulations. In addition, Yi and Wilson (2016) claim that end-of-year forecasts contain noisiness

[7] See (Balsam et al. 2003; Behn et al., 2008; Beasley and Petroni, 2001) for industry specialization used for a high quality audit.

$$\text{AFE}= \frac{|Median\,Forecasts - Actual\ EPS|}{Share\ price}$$

Forecast dispersion (*DISP*) is defined as the standard deviation of all earnings forecasts issued by all analysts following the same firm.

$$\text{DISP}= \frac{STD\,(Forecasts)}{Share\ price}$$

Forecast Revision (*REVISION*), following the approach of Barth and Hutton (2004), is calculated as last consensus forecast minus first consensus forecasts and is then scaled by the share price at the end of the last year.

$$\text{REVISION}= \frac{|LF - FF|}{Share\ price}$$

Where the first forecast (FF) is the first one which is made after the last year's earnings announcement date; The last consensus forecast (LF) is calculated using all available forecasts made before the current year's earnings announcement; All forecast properties are calculated based on forecasts issued between the last year's earnings announcement date and the current year's earnings announcement date.[8]

3.1.2 Measurement of Accounting Complexity

There is no formal definition of "complexity" in extant accounting literature {Baudot, 2018 #1816}, however, prior research measured and examined complexity from different perspectives. For instance, one perspective tries to measure complexity by looking into the volume/length of the annual reports or its readability by using Gunning Fog Index (GFI) or other lexical methods (Lehavy, 2011; Li, 2008). Another perspective examined information complexity (e.g., Plumlee, 2003; Peterson, 2012). Plumlee (2003) measured complexity arising from the changes in tax -laws and how it affects financial analysts. Peterson (2012) examined the impact of complexity associated with revenue recognition and they found that revenue restatement increases due to such complexity.

Recently, Baudot (2018) measured complexity based on comment letters submitted to the Financial Accounting Standards Board (FASB). More specifically, they investigate the

[8] For example, Ansell Limited follows a July-June fiscal period and announces their earnings for 2004-05 on 17 August 2005 and their current year earnings (2005-06) on 24 August 2006. Forecasts which are issued after 17 August 2005 and before 24 August 2006 are considered in calculating forecast properties.

accounting profession's engagement in complexity taking a viewpoint of multiplicity, diversity, and interrelatedness on comment letters submitted to FASB.[9] By investigating 864 comment letters submitted by only Big 4 firms in the last 12 years, they found that firms mainly oppose a change when they believe it may increase complexity. However, they conclude that Big 4 audit firms do not hold universal opinion regarding the main causes of complexity. Taken together, it is clear that there is no single measure of complexity. The present study measures complexity by using a quantitative proxy which is considered an objective measure by prior research (Baudot, 2018). In this study, a complexity score is measured for each standard for each sample company. AASB 1047 requires an entity shall disclose an explanation of how the transition to Australian equivalents to IFRS is being managed and a narrative interpretation of the key differences in accounting policies that are expected to arise from the adoption of A-IFRS in its financial reports (para 4.1a and b, AASB 1047). The above information is fairly and comprehensively available in AGAAP-IFRS reconciliation statements. Another standard, AASB 1 also requires that the first-time adopters of Australian equivalents to IFRS should provide comprehensive reconciliation statements showing their financial performance and financial position under the two accounting systems, the old AGAAP and the new AIFRs (AASB 1, 2004a). We measure complexity based on the magnitude of the adjustments made in the reconciliation statements, prepared in the year of IFRS adoption. The main-focus of our study is on individual accounting standards. Firstly, we identify six accounting standards that are found to have a significant impact on financial statements in prior Australian accounting studies (De George et al., 2013; Jermakowicz & Gornik-Tomaszewski, 2006; Jubb, 2005). These standards includeAASB2 *Share-based payments*, AASB 3 *Business Combinations*, AASB 136 *Impairment of Assets*, AASB 138 *Intangible Assets*, AASB 112 *Income Taxes*, and AASB 119 *Employee Benefits.* Although some other studies, for instance, Haswell (2008) identified 57 defects in IFRS and their findings were heavily criticized by Bradbury (2008) and Nobes (2008). Moreover, the latter two authors claim these defects as "may be personal assertions". These findings for Australia are largely consistent with findings for other comparable jurisdictions such as New Zealand (for example Stent, Bradbury, & Hooks, 2010) and Germany (e.g., Hung & Subramanyam, 2007).

In our data collection phase, some additional IFRS standards are identified as being complex because many firms make substantial reconciliation adjustments that arise from these

[9] Baudot et al. (2018) take the concept of complexity, more specifically, multiplicity, diversity, and interrelatedness from prior complexity research (e.g., Jacobs, 2011; Jacobs, 2013).

standards. These additional standards include AASB 116 *Property, Plant and Equipment,* AASB 117 *Leases,* AASB 121*The Effects of Changes in Foreign Exchange Rates,* AASB 132 *Financial Instruments: Presentation,* AASB 139 *Financial Instruments: Recognition and Measurement, and* AASB 140 *Investment Property*. We define those standards as new standards. Recently, Barth et al. (2014) investigated the value relevance of reconciliation adjustments for net income (NI) with the stock price. They consider the aggregate impact on NI from 11 IFRS standards and find that the resulting net income adjustments are incrementally value relevant for both financial and non-financial firms. Our study, therefore, extends the list of complex standards to include 9 of the 11 standards identified by Barth et al. (2014).[10]

For each standard, the differences in affected accounts (for instance, amortization, share-based payments, etc.) from IFRS reconciliations are collected. These differences are then measured as a percentage of either Total Revenue if the account is a statement of comprehensive income item or Total Assets if the account is a statement of financial position related item. We classify those differences into four categories (i.e., ‘Material', ‘Moderate', ‘Small' and ‘Zero') based on materiality thresholds used in auditing practice (Leung, Coram, Cooper, & Richardson, 2015, pp. 41-420). That is, the difference is considered as *Material* if it is 1% or more of either Total Revenue or Total Assets; as *Moderate* if it is in between 0.5% and 1% of the above totals; as *Small* if it is less than 0.5% but greater than 0; and as *Zero* where there is no difference as a result of the switch to IFRS. We use those categories for complexity scoring (i.e., 6 is assigned for material, 4 is assigned for moderate, 2 is assigned to small and 0 is for no adjustments). For instance, Avexa Limited (Official Ticker: AVX) prepared a reconciliation statement showing the impact of AASB 2 *Share-based Payment* (see Appendix-B). It has shown that due to IFRS adoption, the company had an additional AU $61000 as an expense adjustment, which is 9 percent of the Total Revenue of Avexa Limited. Based on the above materiality thresholds, as it is more than 1 percent of turnover this is a material adjustment, we assign 6 points for this adjustment. Another example using a statement of financial position related item is that of BKM Management Limited (Official Ticker: BKM) reporting on the impact of AASB 136 *Impairment of Assets* (see Appendix-B) in its

[10]Barth et al. (2014)’s 11 standards are IAS 39IFRS 3, IAS 19, IFRS 2, IAS 2, IAS 12,IAS 16, IAS 17, IAS 37, IAS 38 , other. The present study's list of complex standards covers all of the standards covered by Birth et al. (2014) except IAS 2, IAS 37 and other (undefined). However, the present study found some other standards such as IAS 121, IAS 32, and IAS 40 (categorized under "additional six standards"), and IAS 36 (listed under"original six") are complex which were not considered in Birth et al. (2014). Undoubtedly the present study will provide better insights about the impact of reconciliation adjustments arising from both original and additional standards on analyst forecast properties.

reconciliation. Specifically, there is a reversal of amortization of AU$ 71,144 due to the changes from the amortization approach under old AGAAP to the approach of impairment testing under IFRS. To calculate complexity induced by AASB 136, we deflate this adjustment by total assets, which returns a value of 8.77%, again resulting in a 'material' score of 6 points. A high score indicates a high level of complexity because material adjustments have been made on that account due to the adoption of IFRS.

When we consider all the original six accounting standards together, it represents the complexity scores assigned to individual standards which are aggregated by firms. For instance, Insurance Australia Group Limited (IAG) shows that their financial statements as of June 30, 2006, are affected by AASB 2 *Share-based Payment* (percentage of total revenue is 0.000457, which is given score 2), AASB 136 Impairment of Assets (total value of reversal of amortization is 92, 000 which is 0.005369 percent to total assets; a score of 4 is assigned as it is in between 0.5% to 1.0%), AASB 138 Intangibles Assets (adjustment amount is 24,000 which is 0.001401 percent to total assets, which can be categorized as small adjustment and a score of 2 is assigned), AASB 112 Income Taxes (total value of adjustments is 0.019228 which falls under material adjustment category and it is given a score of 6), and finally, AASB 119 Employee Benefits (value of adjustment is 80023 which is 0.012195 percent to both total assets and the total revenue; a score of 6 is given as this percentage falls under category 1). If we sum up all the scores of IAG companies, it shows its total score is 20).

As a result, IAG Limited's total complexity score of five complex standards scores is 20. Using the same approach, we measure complexity as (i) aggregate composite complexity score of original six complex standards; (ii) the composite complexity scores of original six complex standards separately; (iii) aggregate composite complexity score of 12 standards including new six standards that are identified during data collection phase; and (iv) the composite complexity scores of 12 standards separately.

Empirical tests are then conducted with all four complexity measures. We have matched the complexity dataset with the analyst forecasting dataset to have a common sample.

3.2 Research Design

The first three hypotheses [H1-H3] are empirically tested using Model 1 below. The model is based on empirical models of Bae et al. (2008), Barth and Hutton (2004), Byard et al. (2011), and Horton Horton et al. (2013).

$$
\begin{aligned}
FORECAST\_PROPERTIES \\
&= \beta_0 + \beta_1 \text{COMPLEXITY} + \beta_2 \text{SIZE} + \beta_3 \text{FOLLOW} + \beta_4 \text{SURPRISE} \\
&+ \beta_5 \text{HORIZON} + \beta_6 \text{RETVOL} + \beta_7 \text{NUMEST} + \beta_8 \text{AGE} + \beta_9 \text{EARNSD} \\
&+ \beta_{10} \text{ROA} + \beta_{11} \text{STOCKTURNOVER} + \text{YEAR DUMMIES} \\
&+ \text{INDUSTRY FIXED EFFECTS} + \varepsilon \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots ... \ldots \ldots (1)
\end{aligned}
$$

Where *FORECAST_PROPERTIES* are measured as analyst forecast errors (*AFE),* forecast dispersion *(DISP),* and forecast revision *(REVISION),* respectively. *COMPLEXITY,* the variable of interest, is measured using four different measurement methods: (i) a composite complexity score of all original six complex standards (*COMPLEXITY_6SD*); (ii) the original six complex standards individually (for instance, *COMPLEXITY_AASB2* indicates the complexity score derived based on complexity arising from AASB 2 *Share-based Payment*; *COMPLEXITY_AASB136* indicates the complexity arising from AASB 136 *Impairment of Assets*); (iii) a composite complexity score of a full set of twelve standards identified as complex (*COMPLEXITY_12SD* indicates the aggregate complexity scores from all IFRS considered in this study); and (iv) the twelve standards individually. The control variable definitions are available in Appendix-A.

Analyses on forecast error, dispersion and revision share the same set of complexity and control variables, expect for forecast horizon (*HORIZON*). The forecast horizon is not used in revision analysis following prior studies.

We expect the coefficients on *COMPLEXITY* variables to be positive for forecast error, dispersion and revision analyses.[11] With respect to the control variables for all cases, we expect the coefficients on *SIZE* to be negative because forecast errors and dispersions are lower for larger firms and fewer forecast revisions for larger firms (Lang and Lundholm, 1996). Prior research by Lang and Lundholm (1996) find a positive association between *SURPRISE* and all forecast properties**.** We expect negative coefficients for analyst following *(FOLLOW)* with

[11] *COMPLEXITY_IFRS* means complexity for all standards considered in this study. For instance, it includes *Complexity_AASB2, Complexity_AASB3*, etc.

respect to forecast errors but positive coefficients with forecast dispersion, because the greater the analyst following for a firm, the smaller the forecast errors and forecast dispersions tend to be (Bhushan, 1989), along with the forecast revisions being fewer. Following Brown (2001b), this study controls *HORIZON* for both forecast error and dispersion analysis, because it is expected that a forecast announced closer to the actual earnings announcement date is closer to actual EPS; hence, it has lower forecast error and lower dispersion than those announced earlier in the year. Return volatility *(RETVOL)* and earnings variability *(EARNSD)* are normally used as proxies for uncertainty in a firm's future performance. We expect the coefficients of both variables to be positive for all forecast properties, as firms with more volatile past earnings and stock returns tend to have less disclosure, which increases information asymmetry among analysts, thereby increasing forecast errors, dispersion, and forecast revisions (Lang & Lundholm, 1996). For the number of estimates *(NUMEST)* in regression models, we expect that as the higher the number of forecasts issued by all analysts for a firm, the higher would be the forecast errors, dispersion, and frequency of revisions (Jiao et al., 2012). Following Matolcsy and Wyatt (2006), we expect *AGE*, the number of years the firm has been listed in the ASX, to have positive coefficients for all three of our dependent variables, implying that the longer the firms are listed, the greater the tendency to have higher forecast errors, higher dispersion, and more frequent revisions.

The profitability indicator variable *(ROA)* is included as analysts' forecasts more profitable firms have, on average, fewer forecast errors than loss-reporting firms (Lang and Lundholm, 1996). Finally, we control stock turnover *(STOCK TURNOVER)* following Tan et al. (2011) and expect negative associations implying that firms having greater market liquidity or turnover produce positive signals to market participants thereby decreasing forecast errors and forecast dispersion.

To test whether ISP has moderating effects on the association between complexity and forecast properties, we follow two approaches. The first approach is to investigate whether there is any moderating effect of ISP on the relation between accounting complexity and forecast properties (Model 2). We contend that high quality auditors can provide high quality accounting information (Francis and Yu, 2009), that may increase the confidence of users of accounting information, in this case, financial analysts.[12] We use both city-level industry

[12] In Eq. (2), *COMPLEXITY* is replaced by *COMPLEXITY_AASB132* and *COMPLEXITY_AASB2* for AFE analysis, *COMPLEXITY_AASB138* and *COMPLEXITY_AASB117* for forecast dispersion and *COMPLEXITY_AASB138* and *COMPLEXITY_AASB117* for forecast revision. All other control variables are similar to the ones used in Eq. (2)

specialists (*CITY_ISP)* and national-level ISP (*NATIONAL_ISP*) as proxies of high quality audit.

$$FORECAST\_PROPERTIES = \beta_0 + \beta_1 \mathrm{COMPLEXITY} + \beta_2 \mathrm{ISP} + \beta_3 \mathrm{COMPLEXITY} * \mathrm{ISP} + \beta_4 \mathrm{SIZE} + \beta_5 \mathrm{FOLLOW} + \beta_6 \mathrm{SURPRISE} + \beta_7 \mathrm{HORIZON} + \beta_8 \mathrm{RETVOL} + \beta_9 \mathrm{NUMEST} + \beta_{10} \mathrm{AGE} + \beta_{11} \mathrm{EARNSD} + \beta_{12} \mathrm{ROA} + \beta_{13} \mathrm{STOCKTURNOVER} + \mathrm{YEAR\ DUMMIES} + \mathrm{INDUSTRY\ FIXED\ EFFECTS} + \varepsilon. \dots\dots\dots\dots\dots\dots (2)$$

Next, we conduct sub-sample analysis to test whether the effect of ISP (at both city-level and national-level) using Model 3 on forecast properties differs between firms with high and low complexity. To this end, we divide the whole sample into two groups based on the aggregate complexity level using either six standards' aggregate score and the aggregate score of all 12 standards identified.

$$FORECAST\_PROPERTIES = \beta_0 + \beta_1 CITY_{ISP} + \beta_2 \mathrm{SIZE} + \beta_3 \mathrm{FOLLOW} + \beta_4 \mathrm{SURPRISE} + \beta_5 \mathrm{HORIZON} + \beta_6 \mathrm{RETVOL} + \beta_7 \mathrm{NUMEST} + \beta_8 \mathrm{AGE} + \beta_9 \mathrm{EARNSD} + \beta_{10} \mathrm{ROA} + \beta_{11} \mathrm{STOCKTURNOVER} + \mathrm{YEAR\ DUMMIES} + \mathrm{INDUSTRY\ FIXED\ EFFECTS} + \varepsilon \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

Where,

CITY_ISP = indicates city-level industry specialisation. Following Krishnan et al. (2013), we use the audit market share to measure city level industry specialization. To add robustness to the results, we also use national level ISP. We also measure industry specialist in both city and national levels as joint specialist auditors (*JOINT_ISP*). To identify specialization, we follow the following procedure. First, the location of audit firms is identified for all sample companies. Then, the total audit fees of each audit firm in each industry and in each of the five cities (e.g., Adelaide, Brisbane, Perth, Melbourne, and Sydney) are calculated. The audit firm with the highest audit revenue in a particular industry and a particular city is ranked as a city-level ISP. This procedure is repeated for national-level ISP. Finally, joint ISP is identified by identifying which auditors are specialists at both city and national levels.

Although a testable hypothesis for Model 3 we contend that for the sub-sample analysis partitioned on the level of complexity, forecast error and forecast dispersion will be significantly lower for firms with a higher complexity level compared to those with a lower complexity level, conditional upon the firms being audited by an ISP. It is expected the coefficient on *CITY_ISP* will be negative for all forecast properties, as our expectation is that high quality auditors (*CITY_ISP*) will increase financial reporting quality, mitigating the effect of complexity on analyst forecast errors, dispersion, and revision.

3.3 Data and Sample Selection

The sample comprises firms listed in the Australian Stock Exchange (ASX). Analyst forecast data are collected from Institutional Brokers Estimate System (I/B/E/S). Actual EPSs and data for measuring control variables are collected from COMPUSTAT Global database and DataStream. Data used to measure complexity are manually collected from annual reports filed and published on ASX listing web page. *I/B/E/S* gives analyst forecast data for 6915 forecasts made for 442 firms in 2005. After matching with complexity dataset, 327 firms are kept. Then, we eliminate firms with unavailable data. This results in a sample of 322 observations with the required financial statement and complexity data. In Table 1, Panel A shows the sample derivation and Panel B shows the whole sample breakdown industry-wise.

[TABLE 1ABOUT HERE]

To investigate the moderating effect of industry specialization, we identify how many companies are located in the big 5 cities in Australia. We find that 287 out of the 322 firms are audited by city level industry specialist auditors for forecast error analysis, 240 firms for dispersion analysis, and 214 firms for forecast revision analysis. Table 4 (Panel A) shows the detailed descriptive used for moderating analysis. Panel B of Table 4 shows the correlation statistics for variables used for moderating analysis. Next, we divide our whole sample into two sub-samples as high complexity and low complexity groups (based on mean complexity (for both aggregate of six and aggregate of 12 standards). We follow the same classification for both the aggregate of six complex standards (Panel A, Table 5) and for the aggregate of all standards (Panel B, Table 5) considered in this study.

4. Empirical Results

4.1 Descriptive

In Table 2, Panel A presents univariate statistics for all the variables. The mean value of forecast errors (*AFE*) is 0.048, suggesting that the difference between analysts' forecasts and corresponding actual earnings is about 4.8% of the lagged stock price. The mean dispersion (*DISP*) is 0.023, which suggests that the average forecast dispersion is about 2.3% of the lagged stock price. On the other hand, the mean value of forecast revision (*REVISION*) is 0.034 which suggests that the average forecast revision is 3.4% of the lagged stock price.

The means of the individual standards-based *COMPLEXITY* variables have noticeable variations suggesting with AASB3 having the lowest and AASB112 having the highest means. As expected, the combined means of the standards reflected in the aggregate variables, *COMPLEXITY_6SD* and *COMPLEXITY_12SD* are much higher than that of its constituents, the individual standards, at 9.335 and12.385, respectively.

Firm size, which is the logarithm of market capitalization (*SIZE*), has a mean of 5.889. The mean of analyst following (*FOLLOW*) is 1.569, implying that on average; four analysts are following a firm included in the final sample. The average earnings surprise (*SURPRISE*) is 0.065. The mean of the forecast *HORIZON* is 5.225, implying that the average number of calendar days between the forecast announcement date and the subsequent actual earnings announcement date is 200. *RETVOL* measures the variations of weekly stock returns for a firm at t-1. The mean of *RETVOL* is 0.077.

The mean of estimates (*NUMEST*) made by analysts is 2.213, which indicates that at least 9 forecasts have been made for the sample firms. The minimum and maximum value of *NUMEST* is 0, and 4.663 respectively. It means some firms have only one forecast estimate in the sample period, whereas the highest number of estimates is 106. The average listing period of the firm (*AGE*) is 2.181. On the other hand, *EARNSD* measures the standard deviation of firms actual EPS over the last three years. The mean value of *EARNSD* is 0.124 while the median is 0.056. In the regression analysis, this study uses *STOCKTURNOVER*, which shows the number of shares traded in the current year divided by the average number of shares outstanding in the current year. The mean value of *STOCKTURNOVER* is 0.003, implying that on average 1000 shares are traded during the sample period. However, the maximum number of shares traded is 1010. Descriptive statistics are not reported for Year (*Ye*) and Industry Classification

(INDUSTRY FIXED EFFECTS) statistics for the variables are not tabulated in the interests of parsimony.

Panel B presents the Pearson correlation matrices for the regression variables. We find a positive correlation between *COMPLEXITY_AASB2*, *COMPLEXITY_AASB116* and analyst forecast errors and dispersion. Similarly, we get positive associations between *COMPLEXITY_AASB138*, *COMPLEXITY_AASB139*, and *COMPLEXITY_AASB117* with both forecast dispersion and forecast revision. All other complexity variables show correlations in the opposite direction. However, forecast error is positively associated with both forecast dispersion and forecast revision. For control variables, firm size (*SIZE)* is negatively correlated with all forecast properties but statistically significant with *AFE* and *DISP* only. *SURPRISE* is positively and significantly correlated with all forecast properties. The profitability measure, return on assets *(ROA*), is negatively and significantly correlated with both forecast error and dispersion but positively associated with forecast revision. The earnings variability measure (*EARNSD*) is positively associated with all forecast characteristics but statistically significant only with respect to forecast error and forecast revision. Finally, the firms' performance uncertainty measure, *RETVOL*, is positively associated with all forecast properties but statistically not significant.

4.2 Regression Results

Table 3 presents multivariate regression results for Model 1 that examines the effect of complexity on forecast properties. Ordinary Least Square (OLS) regressions results are shown, in four columns for each analyst forecast property, respectively with (i) the composite complexity score of all original six complex standards; (ii) the original six complex standards separately; (iii) the composite complexity score of the full set of 12 standards identified as complex; and (iv) the 12 standards identified separately. In general, the results show no discernible effect of complexity measured in aggregate as evidenced by the results for *COMPLEXITY_6SD* and *COMPLEXITY_12SD* in columns 1, 3, 5, 7, 9, and 11. However, results for s of the individual complex standards do yield significant results – these have been highlighted in bold letters for ease of identification. This suggests the importance of decomposing complexity into individual standards. Columns 1 and 3 show the impact of aggregate complexity on AFE. Measuring the complexity of multiple standards in the aggregate may, therefore, mask the effect of specific standards.

The results for individual complex standards are presented in columns 2, 4, 6, 8, 10, and 12. Column 2, Table 3, shows the impact of individual standard complexity on *AFE* with the original six standards being included in the model specification simultaneously. *COMPLEXITY_AASB2* (AASB 2 Share-based Payments) and *COMPLEXITY_AASB132* (AASB 132 *Financial Instruments: Presentation*) are positively and significantly associated with *AFE* (for AASB 2, coefficient 0.005, at least t-statistic 2.18, and significant at the better than 5% level; while for AASB 132, coefficient 0.008, t-statistic 3.26, significant at the better than 1% level). AASB 2 requires an entity to disclose how they determine the fair value of the goods or services received, or the fair value of the equity instruments granted. Measuring the fair value of equity instruments is challenging, requiring subjective judgment which creates bias and information noise. For instance, complex stock option pricing models are often used by firms to calculate fair values of equity instruments specified in the equity settled share-based payment transactions (AASB, 2004d; para 46). However, even experienced accountants and financial analysts find it difficult to comprehend and evaluate the suitability of a particular pricing mode (De George et al., 2013). In addition, entities need to explain any alternative methods used, where the fair value method is impracticable. This will again increase the complexity for financial analysts.

Our study confirms that fair value measurements, along with a discretionary choice for option pricing models for share valuation, increase AFE. This is consistent with prior research findings (Lihong and Riedl, 2014). Lihong and Riedl (2014) argue that the fair value method, which allows recognition of unrealized gains and losses, increases analyst forecast errors because financial analysts do not eliminate those losses and gains in making their forecasts. More specifically, they suggest that analysts face greater difficulty in forecasting statement of comprehensive income-based elements which have a low serial correlation.

Similar arguments apply for AASB 132 *Financial Instruments: Presentation*. This standard requires firms to disclose descriptions of the financial instruments, their carrying amount and an explanation of why fair value cannot be measured reliably (AASB, 2004b). In addition, this standard requires firms to disclose assumptions used in valuation along with financial risk profiles. However, these disclosures involve complexity and require subjective judgments due to the lack of active and liquid markets. The complexity and uncertainty inherent in these disclosures may, therefore, also result in increased forecast errors.

For forecast dispersion analysis (columns 5-8), the coefficient of *COMPLEXITY_AASB138,* when we consider only the original six complex standards, is positive and significant at $p<0.10$. Although the significance of this finding is lost when we consider the new six standards identified as complex, it nevertheless suggests that complexity arising from AASB 138 *Intangibles Assets* increases forecast dispersion. Significant changes in intangible accounting standards were brought about by AASB 138 in Australia (e.g., capitalization of development expenditure; need to demonstrate the technical feasibility of developing assets available for use or sale and the probability of generating future economic benefits) (AASB, 2004c). Therefore, making decisions about the capitalization of expenditure requires accountants' judgment and managerial discretion. When subjectivity is involved, external information users may perceive greater levels of information asymmetry, resulting in uncertainty and dispersion in predicting firms' future prospects. High uncertainty is innate to intangibles due to their abstract nature. Also, information on the likelihood of technological success may only be observable by insiders, which accentuates information asymmetry. Various feasible explanations can, therefore, be put forward to support this finding of a significant and positive effect of complexity pertinent to intangible accounting standards on analyst forecast dispersion.

The results in Column 8 show that when the additional six standards, under the new six standards categories, are added in regression mode 1, *COMPLEXITY_AASB117* relating to AASB 117 *Leases*, is positively and significantly related to *DISP* ($\beta = 0.007$ with $t = 2.14$). Adjustments required for leases in reconciliation statements, increase uncertainty about a firm’s future performance, which results in high analyst forecast dispersion.

Somewhat surprisingly, there are significant negative coefficients on *COMPLEXITY_AASB136* and *COMPLEXITY_AASB116*, suggesting that forecast dispersion decreases among the analysts when there is complexity as proxied by a high reconciliation adjustment as a result of these standards. The new IFRS-based accounting standard, AASB 116 *Property, Plant and Equipment* (PPE), brought significant change compared to previous accounting standards. For instance, prior accounting standards relating to PPE (such as AASB 1015 *Acquisitions of Assets*, AASB 1021 *Depreciation*, and AASB 1041 *Revaluation of Non-Current Assets*) were applicable to both tangible and intangible assets (AASB, 2004f). After adopting IFRSs, one standard (AASB 116) concerns only tangible assets, while intangible assets are now governed by a separate new standard (AASB 138 *Intangible Assets*). This new standard is more specialized and contains clear guidance, resulting in improved disclosure. In addition, the new standard contains stricter requirements for entities to disclose the use of the revaluation model for individual assets as opposed to the cost model. These changes may enhance the analyst information environment thereby reducing dispersion among analysts.

Lastly, for forecast revision analysis, results from the analysis of the original six complex standards (Column 10) shows that none of the standard's complexity is positively associated with analysts' forecast revision except *COMPLEXITY_AASB136*, which shows the opposite direction. It may be due to the fact that analysts' uncertainty is reduced as a result of a change to the impairment approach promulgated in AASB 136, as opposed to the prior straight-line amortization approach under AASB 1010 *Recoverable Amount of Non-Current Assets* and AAS 10 *Recoverable Amount of Non-Current Assets*. This is consistent with literature that the new impairment approach provides more useful information compared to the amortization method, thereby enhancing analyst forecast performance (Chalmers et al., 2012).

The extended analysis including the additional new six standards (column 12) confirms that *COMPLEXITY_AASB117* is positively and significantly associated with analyst forecast revision. Surprisingly, *COMPLEXITY_AASB3* is identified in this analysis as positive and significant at the 5% level. Goodwill treatment was significantly changed after IFRS adoption as AASB 3 requires entities to ensure the valuation of all identifiable assets, both tangible and intangible, at fair value, which is subject to the assumptions and judgments of preparers (AASB, 2004e). In addition, the determination of fair value is not always straightforward due to unavailability of active markets for the net assets of a whole business (Barth & Landsman, 1995). This limitation increases information asymmetry between firms and their analyst following, thereby increasing the frequency of forecast revisions.

With respect to the control variables, *SIZE* is the only variable consistently significant and showing a negative coefficient in all forecast properties, suggesting that analyst forecast errors, forecast dispersion, and frequency of forecast revision are lower for larger firms which is consistent with prior research (Brown, Richardson, & Schwager, 1987c; Lang & Lundholm, 1996). This is because analysts are more interested in larger firms. *SURPRISE* is positively and significantly associated with all forecast properties, except forecast revision. This indicates that changes to firms' actual earnings from last year to the current year have a significant influence on forecast errors and the standard deviation of firms' forecasts (Lang & Lundholm, 1996). In the case of forecast revision analysis, the control variable *NUMEST* has positive and significant associations with forecast revision, implying that the greater the number of forecast estimations for a firm, the greater the incidence of forecast revisions. Other control variables exhibit less explanatory power.

Overall, the results do not support an association between aggregate complexity arising either from the original six complex standards, or aggregate of original six and additional six complex standards (i.e. 12 standards in total) and the properties of analysts' forecasts. However, the individual standard analyses using decomposed complexity scores reveal insightful findings. These findings support the argument that aggregate scores are neither good at capturing IFRS benefits/costs, nor capable of uncovering specific effects of individual standards on information users. This is in line with critics of the use of dummy variables to investigate IFRS effects. Using a dummy variable approach (i.e., pre- and post-IFRS years are labelled as 0 and 1), Tan et al. (2011) reach a similar conclusion that local analyst forecast accuracy does not improve due simply to IFRS adoption. Cotter et al. (2012) report similar results with respect to forecast dispersion.

[TABLE 2 ABOUT HERE]
&

[TABLE 3 ABOUT HERE]

4.3 Regression Results for the Moderating Effect of Audit Quality

To see the moderating effects of audit quality on the relation between accounting complexity and analyst forecast properties, we estimate Model 2 by interacting complexity with audit quality (proxied by ISP). However, we do not find any moderating effect of ISP on the association between accounting complexity and analyst forecast properties using Model 2 (results un-tabulated). Next, under the second approach, to have finer insights whether ISP's moderating effect differs between high complexity group of companies and low complexity group of companies. To do so, we partition sample observations into the highly complex and low complex –sample groups. Regression analyses using Model 3 are conducted for each sub-sample. The aggregate complexity score of both six standards (together) and of 12 standards (together) are used in order to classify the sample into high and low complexity groups. A total of 144 firms and 129 firms are classified as high complex firms under six and 12 standards respectively.[13] In both cases, Model 3 is analyzed to regress forecast properties on both city-level and national-level ISP and a set of control variables. The results are reported in Table 5.

Table 5 shows the sub-sample analysis. Panel A (Panel B) is based on aggregate scores of the original six standards (12 standards together). For city-level ISP, Panel A reports the coefficient of *CITY_ISP*, regarding forecast error (*AFE*), as significant at the 5% level and negative (-0.017) for only the high complexity firms. In comparison, this effect is insignificant for low complexity firms. The results suggest a decrease in analyst forecast errors (*AFE*) for firms audited by city level ISPs, but only when firms face high levels of complexity during IFRS adoption. The result is stronger when using the aggregate complexity score of the original six standards than when using the aggregate complexity score of all 12 standards.

For forecast dispersion analysis, ISP shows no moderating effect for either high complexity or low complexity firms. However, the coefficient of *CITY_ISP*, for forecast revision analysis in Panel B, is negative for low complexity firms, suggesting that the incidence of analyst revisions is reduced where firms have lower levels of complexity and are audited by city level ISPs. Nevertheless, no moderating effect of national level ISP is found on the association between accounting complexity and forecast properties (un-tabulated).

[TABLE 4 ABOUT HERE]
&
[TABLE 5 ABOUT HERE]

5. Additional Analyses

An alternative measure of audit quality

We re-estimate the models using Big Four (*BIG4*) instead of ISP as a proxy of audit quality to see whether BIG4 and ISP are affecting the analyst forecasting abilities identically or not. Our results (un-tabulated) show that there is no effect of Big 4 audit quality on the association between aggregate complexity of six and twelve standards on analyst forecast properties, which is consistent with our main analysis. A similar result is found when we interact Big4 with individual standard complexity in our regression models.

[13] Mean score for six standards together is 9.43 and 12.38 for an aggregate score of 12 standards.

Sub-sample analysis

In our main analysis, we partition our full sample into two samples (based on aggregate complexity) to see the moderating effect of industry specialization (shown in Table 5). In this case, we replace by Big4 for city-level ISP (*CITY_ISP*) to see whether the audit quality (proxied by Big4) reports better results on the association between complexity and analyst forecast properties. We don't find any surprising results except for sub-sample analysis based on the aggregate of the twelve standards (only for Revision Model) where the coefficient of Big 4 (BIG4) is found negative, which suggests that analyst forecast revision decreases if the firm is audited by big 4 audit firms. However, the results hold for firms which are exposed to lower levels of complexity.

Complexity scoring alternatives

To validate our assignment of different scores to different levels of complexity associated with different accounting standards (0, 2, 4, 6 for zero, small, moderate and material level of complexity respectively), we re-run our regression by replacing with 0,1,2,3 for zero, small, moderate, and material level complexity. We find that our results (un-tabulated) are consistent those of the main analysis, which suggests that our assignment of different scores for different levels complexities are not suffering from scaling biases.

6. Conclusions

We examine the impact of complexity arising from IFRS adoption on financial analysts forecast properties and also test whether this effect of complexity on analyst forecast property varies with audit quality. While several prior studies (e.g., Byard et al. 2011; Horton et al. 2013) examine the impact of mandatory adoption of IFRS on the information environment of firms (mainly analyst forecast errors/dispersion), this study contributes to the literature by disentangling total IFRS impact into its components, individual IFRS impact on analyst forecast properties including forecast errors, forecast dispersion and forecast revision.

We find that only two standards *(*AASB 2 *Share-based Payment* and AASB 132 *Financial Instruments: Presentation*) are positively and significantly associated with analyst forecast errors, AASB 117 *Leases* is positively and significantly associated with analyst forecast dispersion. AASB3 *Business Combinations* and AASB 117 *Leases* are found to contribute to increased incidence of analyst forecast revisions in the IFRS adoption period. Our study also finds that forecast errors decrease for high complex firms if they are audited by a city-level industry specialist audit firm, whereas no such evidence is found for either forecast dispersion or forecast revision.

This study is subject to a few caveats, so readers should be cautious about interpreting and generalizing the results. First, our study does not cover all IFRS standards issued by IASB and adopted by Australia because few Australian studies (e.g., De George et al., 2013, Jubb, 2005, Cotter et al., 2012, Pawsey, 2006) identified certain IFRS standards are relatively more complex and require additional attention of accounting information users. However, this study overcomes the limitations of those prior studies and provides a finer way of measuring complexity and investigates the impact of the complexity on one of the important users of accounting information namely financial analysts. Similarly, our study, due to following the above approach, may omit some IFRS standards that may be also complex. Lastly, the relatively small sample size due to a lack of analyst coverage on some companies in the sample. Taken together, our study provides evidence of pitfall associated with first time adopters of IFRS in the lens of analyst forecast performance. We believe that the results, of this study, can be used as evidence by the countries considering adopting or harmonizing IFRS. Moreover, we note that future research can extend our study by investigating the trade-off between the complexity of a certain set of IFRS and benefits of other sets of IFRS and how these trade-off affects/benefits financial analysts.

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Appendix A: Variable Definitions

VARIABLE	DEFINITIONS
AFE	Analyst forecast error (AFE) is measured as the absolute value of the difference between median consensus and actual EPS which is deflated by last year share market price. Firm's actual EPS for the year ended June 30, 2006, is used for companies following fiscal period from July-June and actual EPS of 2005 is used for companies which follow the calendar year (Jan-Dec);
DISP	Dispersion is calculated as the standard deviation of forecasts made for a company. This analysis considers all forecasts made between last year earnings announcement date and current year earnings announcement date. More specifically, it is calculated as the standard deviation of the firm's EPS forecasts, scaled by share price which is at the end of the last fiscal period;
REVISION	The difference of last forecast (LF) of EPS and first forecast (FF) of EPS. If there are multiple forecasts on the same day in both forecasts (first and last Forecast), the average is used;
COMPLEXITY_6SD	The extent of complexity based on complexity measurement for the original six complex standards together;
COMPLEXITY_12SD	The extent of complexity based on complexity measurement for the full set of 12 complex standards together;
COMPLEXITY_AASB2	The extent of complexity based on complexity measurement for AASB 2 Share-based Payment; the same definition applies to all other complexity variables measured based on other 11 other standards individually;
IFRS_DIFF	The extent of complexity measured based on equity difference (AGAAP and IFRS) only;
ROA	The ratio of net profit after tax to ending total assets;
ISP	Auditor industry specialization (ISP) is measured at city-level, national-level and both city and national level (Joint ISP);
SIZE	Natural logarithm of market capitalization for a firm (Chalmers et al. 2012; Matolcsy and Wyatt 2006);
AGE	Natural logarithm of the number of years that a firm has been listed with ASX at 2006 (Chalmers et al. 2012; Matolcsy and Wyatt 2006);
SURPRISE	The absolute value of the difference between the current year's earnings per share and last year's earnings per share, divided by the price at the beginning of the fiscal year (Lang & Lundholm, 1996);
FOLLOW	Natural logarithm of (1 + average number of analysts following a firm), it is calculated starting from last year earnings announcement (LYEA) date to current year earnings announcement (CYEA) date (Chalmers et al. 2012; Matolcsy and Wyatt 2006);
NUMEST	Natural logarithm of (1 + number of analysts' forecasts is included in the consensus forecasts) (Payne, 2008; Cotter et al. 2012);
RETVOL	The standard deviation of weekly stock returns for a firm in the last year (Tan et al. 2011);
EARNSD	standard deviation of the firm's reported earnings over the last three years (Chalmers et al. 2012; Matolcsy and Wyatt 2006);
HORIZON	The natural logarithm of the average number of calendar days between the forecast announcement date and the corresponding actual earnings announcement date (Behn et al., 2008);
STOCKTURNOVER	Number of shares traded in the current year divided by the firm's average number of shares outstanding in the current year (Tan et al. 2011);
YEAR DUMMIES	Indicator variable equal to 1 for firms with a June 30 year-end, otherwise equal to 0;
INDUSTRY FIXED EFFECTS	Industry classification for a firm in the year of 2006 and 2005;

Appendix B: Disclosure of Reconciliation Statements

B-1: Reconciliation of Equity and Net Income (Net Loss) for the year ended 30 June 2005 (ASX: AVX)

Reconciliation of Equity as Presented Under Previous AGAAP to that Under AIFRS.

	30 June 2005 $‘000	1 July 2004 $’000
Total equity under AGAAP	21,112	-
Adjustments to accumulated losses (net of tax):		
Recognition of share-based payment expense	(61)	-
	21,051	-
Adjustments to accumulated losses (net of tax):		
Recognition of share-based payment expense	61	-
Total equity under AIFRS	21,112	-

(a) Reconciliation of Results as Presented Under AGAAP to that Under AIFRS

	2005 $’000
Net loss as reported under AGAAP	13,536
Share-based payment expense	61
Net loss under AIFRS	13,597

Note: Under AASB 2 Share Based Payments, the Company recognizes the fair value of options granted to employees at grant date as an expense on a pro-rate basis over the vesting period in the income statement, with a corresponding adjustment to equity. Share-based payments costs were not recognized under previous AGAAP.

	Note	Previous GAAP	Adjustments on introduction of A-IFRS	A-IFRS
		$	$	$
Revenue		2,072,096		2,072,096
Bad Debts		(8,453)		(8,453)
Audit Fees		(27,450)		(27,450)
Depreciation Expenses		(11,189)		(11,189)
Amortization	2b	(71,144)	71,144	-
Employee Costs		(595,518)	-	(595,518)
Model Agency Costs		(1,552,467)	-	(1,552,467)
Corporate and Administration Costs		(332,490)	-	(332,490)
Occupancy Costs		(98,094)	-	(98,094)
Mineral tenement Acquisition & Exploration Expenditure Written Off	2a	-	(5,909)	(5,909)
Impairment Loss on Goodwill	2b	-	(71,144)	(71,144)
(Loss) before income tax expense		(624,709)	(5,909)	(630,618)
Income tax expense		-	-	-
Net (loss) attributable to members of the parent entity		(624,709)	(5,909)	(630,618)

Table 1: Sample and Industry Distribution

Panel A: Sample Selection

	Observations
Analyst data available in IBES (Firms)	443
Complexity database provides (firms)	1122
Observation after matching	327
Less: Non-availability of horizon variables	5
Total observations used for analysis	**322**
The categorization of the companies based on the fiscal period following:	
Following the July-June Fiscal period	282
Following the January-December period	40
Total firms in the analysis	**322**

Panel B: Distribution of firms across different industries [Ref. GICS industry group (four digit)]		No. of firms in the group
1.	Automobiles & Components	4
2.	Capital Goods	22
3.	Commercial & Professional Services	2
4.	Commercial Services & Supplies	17
5.	Consumer Durables & Apparel	7
6.	Consumer Services	13
7.	Diversified Financials	12
8.	Energy	23
9.	Food & Staples Retailing	2
10.	Food, Beverage & Tobacco	9
11.	Health Care Equipment & Services	15
12.	Household & Personal Products	4
13.	Insurance	5
14.	Materials	63
15.	Media	12
16.	Miscellaneous	6
17.	Pharmaceuticals & Biotechnology	13
18.	Real Estate	33
19.	Retailing	14
20.	Semiconductors & Semiconductor Equipment	1
21.	Software & Services	14
22.	Technology Hardware & Equipment	2
23.	Telecommunication Services	7
24.	Transportation	9
25.	Utilities	13
Total number of companies in the sample		**322**

Table 2: Descriptive Statistics and Correlation Matrix								
Panel A: Descriptive Statistics								
Variables name	**N**	**Mean**	**Median**	**S. D**	**Min**	**Max**	**1st Percentile**	**99th percentile**
Complexity Variables								
COMPLEXITY_AASB2	322	2.087	2	2.032	0	6	0	6
COMPLEXITY_AASB3	322	0.217	0	1.006	0	6	0	6
COMPLEXITY_AASB136	322	2.478	2	2.447	0	6	0	6
COMPLEXITY_AASB138	322	0.733	0	1.710	0	6	0	6
COMPLEXITY_AASB112	322	3.267	4	2.601	0	6	0	6
COMPLEXITY_AASB119	322	0.553	0	1.369	0	6	0	6
COMPLEXITY_6SD	322	9.335	8	5.381	0	26	0	22
COMPLEXITY_AASB121	322	0.894	0	1.833	0	6	0	6
COMPLEXITY_AASB132	322	0.056	0	0.508	0	6	0	2
COMPLEXITY_AASB140	322	0.379	0	1.346	0	6	0	6
COMPLEXITY_AASB116	322	0.671	0	1.546	0	6	0	6
COMPLEXITY_AASB139	322	0.565	0	1.576	0	6	0	6
COMPLEXITY_AASB117	322	0.484	0	1.259	0	6	0	6
COMPLEXITY_12SD	322	12.385	12	6.843	0	32	0	30
Forecast Properties and Control Variables								
AFE	322	0.046	0.017	0.075	0.000	0.407	0.000	0.353
DISP	271	0.023	0.01	0.048	0.001	0.385	0.001	0.385
REVISION	272	0.034	0.012	0.067	0	4.84	0	0.5
SIZE	322	5.922	5.690	1.676	2.0794	9.652	2.0794	9.652
FOLLOW	322	1.593	1.609	0.713	0.693	2.833	0.693	2.833
SURPRISE	322	0.063	0.025	0.107	0.000	0.630	0.000	0.630
HORIZON	322	5.225	5.314	0.441	3.466	5.869	3.466	5.869
RETVOL	322	0.077	0.053	0.060	0.016	0.325	0.016	0.325
NUMEST	322	2.248	2.197	1.107	0.693	4.663	0.693	4.663
AGE	322	2.189	2.250	0.958	0	3.7842	0	3.7842
EARNSD	322	0.126	0.057	0.217	0.002	1.621	0.002	1.621
ROA	322	0.905	0.072	4.886	-22.332	20.058	-21.602	20.058
STOCKTURNOVER	322	0.003	0.003	0.002	0.000	0.010	0.000	0.010
See Appendix A for variable definitions.								

Table 2: CONTINUED

Panel B: Pearson Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	*AFE*	1.00																										
2	*DISP*	.367**	1.00																									
3	*REVISION*	0.04	0.07	1.00																								
4	*COMPLEXITY_AASB2*	0.09	0.02	-0.01	1.00																							
5	*COMPLEXITY_AASB3*	0.00	-0.04	-0.03	-0.05	1.00																						
6	*COMPLEXITY_AASB136*	-.203**	-.204**	-0.04	-0.07	0.08	1.00																					
7	*COMPLEXITY_AASB138*	-0.08	0.11	0.11	0.00	0.07	0.08	1.00																				
8	*COMPLEXITY_AASB112*	-.142**	-0.02	0.00	-0.09	0.03	.186**	.161**	1.00																			
9	*COMPLEXITY_AASB119*	-.110*	-0.04	0.11	-0.01	0.09	.136*	0.07	.149**	1.00																		
10	*COMPLEXITY_6SD*	-.180**	-0.08	0.04	.296**	.265**	.595**	.468**	.634**	.427**	1.00																	
11	*COMPLEXITY_AASB121*	-0.07	-0.04	0.01	0.06	0.05	0.10	.190**	0.07	.242**	.235**	1.00																
12	*COMPLEXITY_AASB132*	-0.01	-0.02	-0.01	-0.02	-0.02	-0.04	0.00	-0.05	.117*	-0.03	0.04	1.00															
13	*COMPLEXITY_AASB140*	0.11	-0.09	0.04	-.173**	-0.06	-0.07	-0.10	-0.03	-0.07	-.172**	-.123*	-0.01	1.00														
14	*COMPLEXITY_AASB116*	0.02	0.01	-0.01	0.01	0.00	-.114*	0.01	0.10	0.07	0.02	0.06	-0.03	-0.09	1.00													
15	*COMPLEXITY_AASB139*	-0.02	0.02	0.09	0.06	-0.04	-0.07	0.05	.112*	.161**	0.09	-0.04	-0.04	-0.01	.115*	1.00												
16	*COMPLEXITY_AASB117*	0.00	.156*	.200**	-0.09	-0.05	0.09	0.10	.161**	0.06	.126*	0.01	-0.04	0.02	0.07	.139*	1.00											
17	*COMPLEXITY_12SD*	-.140*	-0.05	0.09	.213**	.188**	.453**	.428**	.585**	.460**	.861**	.437**	0.04	0.01	.276**	.342**	.333**	1.00										
18	*SIZE*	-.272**	-.307**	0.07	-0.06	0.06	.117*	0.04	.185**	.295**	.220**	.114*	0.02	0.07	0.04	.165**	.154**	.295**	1.00	.117*								
19	*AGE*	-0.01	0.00	-0.04	0.01	-0.02	-0.07	0.11	0.10	.126*	0.08	.171**	0.00	-0.10	0.05	0.07	-0.05	.109*	.117*	1.00								
20	*SURPRISE*	.604**	.380**	.384**	-0.02	-0.01	-.198**	0.00	-.124*	-0.05	-.172**	0.03	-0.03	0.00	0.11	0.00	0.08	-0.09	-.234**	-0.02	1.00							
21	*ROA*	-.168**	-.209**	0.08	-.131*	-0.06	0.10	-0.03	.133*	0.02	0.05	0.08	0.06	0.07	0.02	-0.06	-0.04	0.06	.168**	0.10	-.141*	1.00						
22	*FOLLOW*	-.288**	-.148*	0.11	-.117*	0.04	.190**	.135*	.305**	.331**	.325**	.186**	0.03	-0.04	.117*	.114*	.210**	.392**	.750**	0.09	-.210**	.143**	1.00					
23	*NUMEST*	-.218**	-0.06	0.11	-.112*	0.04	.132*	.115*	.305**	.327**	.293**	.174**	0.04	-0.07	.160**	.118*	.150**	.357**	.708**	.138*	-0.11	.162**	.932**	1.00				
24	*RETVOL*	0.04	0.10	0.08	.117*	.116*	-0.03	-0.01	-0.06	-.118*	-0.01	-0.05	0.07	-0.08	-0.08	-0.06	-0.06	-0.08	-.134*	-.179**	0.04	.136*	-.205**	-.172**	1.00			
25	*EARNSD*	.161**	0.05	.211**	-0.03	0.05	-0.04	0.02	0.07	.180**	0.07	.153**	0.01	0.10	0.00	0.03	0.06	.131*	.214**	0.08	.186**	0.03	.227**	.268**	0.06	1.00		
26	*HORIZON*	-.123*	-0.07	0.02	-0.03	-0.03	.176**	.142*	0.05	0.10	.160**	0.09	0.01	-0.01	0.04	-.125*	0.09	.144**	0.10	0.06	-0.11	-0.06	.267**	.251**	-.288**	0.05	1.00	
27	*STOCKTURNOVER*	0.11	0.05	0.08	0.00	-0.04	-0.10	-.127*	0.04	0.10	-0.05	0.02	-0.03	0.03	0.10	.208**	.147**	0.07	.310**	-0.09	.109*	0.01	.350**	.354**	-0.03	0.08	-0.05	1.00

See Appendix A for variable definitions. **, and * represent statistical significance at the 1%, and 5%, respectively (two-tailed test).

Table 3: Multivariate Tests on The Association Between AFE, DISP, and Revision and Accounting Complexity arising from IFRS (H1, H2, And H3)

$$FORECAST\_PROPERTIES = \beta_0 + \beta_1 \text{COMPLEXITY} + \beta_2 \text{SIZE} + \beta_3 \text{FOLLOW} + \beta_4 \text{SURPRISE} + \beta_5 \text{HORIZON} + \beta_6 \text{RETVOL} + \beta_7 \text{NUMEST} + \beta_8 \text{AGE} + \beta_9 \text{EARNSD} + \beta_{10} \text{ROA} + \beta_{11} \text{STOCKTURNOVER} + \text{YEAR DUMMIES} + \text{INDUSTRY FIXED EFFECTS} + \varepsilon \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)$$

	Expected Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		AFE	*AFE*	*AFE*	*AFE*	DISP	DISP	DISP	DISP	REVISION	REVISION	REVISION	REVISION
INTERCEPT	?	0.081	0.084	0.080	0.084	0.085	0.081	0.086	0.099	-0.000	0.004	-0.000	0.029
		[1.08]	[1.14]	[1.08]	[1.12]	[1.11]	[1.04]	[1.11]	[1.27]	[-0.01]	[0.18]	[-0.01]	[1.27]
*COMPLEXITY_AASB*2	+		0.005**		0.005**		-0.002		-0.002		-0.002		-0.001
			[2.18]		[2.27]		[-1.27]		[-1.05]		[-0.95]		[-0.50]
COMPLEXITY_AASB3	+		0.005		0.005		-0.000		0.001		0.001		**0.004****
			[1.40]		[1.55]		[-0.03]		[0.61]		[0.56]		**[1.99]**
COMPLEXITY_AASB136	+		0.000		0.000		-0.002		-0.002*		-0.003**		-0.003**
			[0.19]		[0.33]		[-1.61]		[-1.67]		[-2.30]		[-2.12]
COMPLEXITY_AASB138	+		-0.001		-0.001		**0.003***		0.003		0.001		0.001
			[-0.93]		[-0.45]		**[1.78]**		[1.49]		[0.79]		[0.57]
COMPLEXITY_AASB112	+		-0.001		-0.001		0.000		-0.000		0.001		0.000
			[-0.52]		[-0.45]		[0.15]		[-0.12]		[0.60]		[0.11]
COMPLEXITY_AASB119	+		-0.002		-0.002		0.001		0.001		0.001		0.001
			[-1.14]		[-0.80]		[0.70]		[0.72]		[0.35]		[0.44]
COMPLEXITY_6SD	+	0.000				-0.000				-0.000			
		[0.44]				[-0.18]				[-0.52]			
COMPLEXITY_AASB121	+				-0.003				-0.001				-0.003
					[-1.43]				[-0.45]				[-1.27]
COMPLEXITY_AASB132	+				0.008***				-0.001				0.002
					[3.26]				[-0.88]				[0.80]
*COMPLEXITY_AASB*140	+				0.001				-0.001				-0.003

					[0.47]				[-0.47]				[-1.23]
COMPLEXITY_AASB116	+				-0.001				-0.003**				-0.004
					[-0.33]				[-2.36]				[-1.62]
COMPLEXITY_AASB139	+				-0.001				0.000				0.003
					[-0.52]				[0.15]				[1.36]
COMPLEXITY_AASB117	+				0.000				**0.007****				**0.010****
					[0.19]				**[2.14]**				**[2.08]**
COMPLEXITY_12SD	+			-0.000				0.000				-0.000	
				[-0.20]				[0.22]				[-0.05]	
SIZE	-	-0.009**	-0.009**	-0.008**	-0.009**	**-0.010****	**-0.008****	**-0.010****	**-0.009****	**-0.015*****	**-0.014*****	**-0.015*****	**-0.016*****
		[-2.13]	[-2.34]	[-2.11]	[-2.31]	**[-2.23]**	**[-2.12]**	**[-2.24]**	**[-2.46]**	**[-2.98]**	**[-2.86]**	**[-3.00]**	**[-3.52]**
AGE	+	0.005	0.005	0.005	0.006	0.002	0.001	0.002	0.001	0.005	0.004	0.005	0.003
		[1.24]	[1.31]	[1.28]	[1.56]	[1.14]	[0.42]	[1.10]	[0.33]	[1.57]	[1.04]	[1.50]	[0.93]
SURPRISE	+	0.303***	0.309***	0.302***	0.313***	**0.100***	**0.088***	**0.100***	**0.081***	0.151	0.142	0.153	0.134
		[4.02]	[4.03]	[3.99]	[3.96]	**[1.92]**	**[1.89]**	**[1.96]**	**[1.92]**	[1.62]	[1.56]	[1.64]	[1.55]
ROA	-	-0.000	-0.000	-0.000	-0.000	-0.002	-0.002	-0.002	-0.001	0.000	0.000	0.000	0.001
		[-0.43]	[-0.20]	[-0.43]	[-0.15]	[-1.45]	[-1.53]	[-1.45]	[-1.30]	[0.52]	[0.55]	[0.50]	[1.06]
FOLLOW	-	-0.018	-0.016	-0.017	-0.014	0.003	0.001	0.003	-0.000	-0.009	-0.012	-0.010	-0.014
		[-0.97]	[-0.85]	[-0.92]	[-0.78]	[0.34]	[0.11]	[0.31]	[-0.04]	[-0.59]	[-0.76]	[-0.62]	[-0.93]
NUMEST	+	0.003	0.006	0.003	0.005	0.008	0.006	0.008	0.007	**0.021****	**0.019****	**0.021****	**0.022****
		[0.31]	[0.53]	[0.32]	[0.49]	[1.53]	[1.15]	[1.52]	[1.40]	**[2.38]**	**[2.12]**	**[2.38]**	**[2.39]**
RETVOL	+	-0.065	-0.088	-0.062	-0.095	0.076	0.098	0.074	0.072	0.102	0.118	0.097	0.071
		[-1.00]	[-1.37]	[-0.98]	[-1.43]	[1.28]	[1.46]	[1.26]	[1.15]	[1.38]	[1.47]	[1.32]	[0.91]
EARNSD	+	0.058	0.060	0.058	0.062	0.005	0.003	0.004	0.004	0.026	0.023	0.025	0.029
		[1.52]	[1.64]	[1.53]	[1.62]	[0.39]	[0.26]	[0.36]	[0.36]	[0.86]	[0.76]	[0.85]	[1.09]
HORIZON	-	-0.007	-0.007	-0.006	-0.008	-0.012	-0.011	-0.013	-0.012	-	-	-	-
		[-0.50]	[-0.55]	[-0.48]	[-0.57]	[-0.91]	[-0.81]	[-0.91]	[-0.87]	-	-	-	-
STOCKTURNOVER		4.590**	4.154**	4.577**	4.301**	0.922	1.253	0.888	0.596	2.967	3.124	2.932	1.717
		[2.27]	[2.05]	[2.26]	[2.10]	[0.67]	[0.92]	[0.64]	[0.45]	[1.34]	[1.43]	[1.32]	[0.84]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
YE	-0.006	-0.006	-0.005	-0.005	-0.002	0.001	-0.002	-0.001	0.027**	0.028**	0.026**	0.023**
	[-0.52]	[-0.52]	[-0.47]	[-0.44]	[-0.13]	[0.10]	[-0.15]	[-0.10]	[2.32]	[2.42]	[2.22]	[1.98]
INDUSTRY FIXED EFFECTS	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
OBSERVATIONS	322	322	322	322	271	271	271	271	272	272	272	272
R-SQUARED	0.47	0.49	0.47	0.49	0.43	0.45	0.43	0.48	0.39	0.41	0.39	0.45
ADJ. R^2	0.40	0.41	0.40	0.40	0.33	0.35	0.33	0.37	0.30	0.30	0.30	0.33

See Appendix A for variable definitions. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels respectively (two-tailed test).

Model (1) *AFE* and original six complex standards are considered together as stand-alone experimental variable Model (2) *AFE* and original six complex standards are considered separately, Model (3) *AFE* and full set of 12 complex standards are considered together as stand-alone experimental variable, Model (4*) AFE* and full set of 12 complex standards are considered separately, Model (5) *DISP* and original six complex standards are considered together as stand-alone experimental variable Model (6) *DISP* and original six complex standards are considered separately, Model (7) *DISP* and full set of 12 complex standards are considered together as stand-alone experimental variable, Model (8) *DISP* and full set of 12 complex standards are considered separately, (Model (9) *RIVISION* and original six complex standards are considered together as stand-alone experimental variable Model (10) *RIVISION* and original six complex standards are considered separately, Model (11) *RIVISION* and full set of 12 complex standards are considered together as stand-alone experimental variable, Model (12) *RIVISION* and full set of 12 complex standards are considered separately.

Table 4: Descriptive statistics for Moderating Analysis

Panel A: Descriptive statistics

Variable	N	Mean	Median	S.D.	Min	Max	1st Percentile	99th Percentile
AFE	287	0.046	0.017	0.080	0	0.517	0	0.402
DISP	240	0.024	0.011	0.050	0.001	0.385	0.002	0.385
REVISION	214	0.039	0.015	0.0752	0	0.50	0	0.50
*BIG4*COMPLEXITY_6SD*	287	7.875	8	6.073	0	26	0	22
COMPLEXITY_6SD	287	9.603	10	5.171	0	26	0	22
BIG4	287	0.812	1	0.392	0	1	0	1
CITY_ISP	287	0.401	0	0.491	0	1	0	1
*COMPLEXITY_6SD*CITY_ISP*	287	4.070	0	6.067	0	26	0	20
NATIONAL_ISP	287	0.341	0	0.475	0	1	0	1
*COMPLEXITY_6SD*NATIONAL_ISP*	287	3.436	0	5.721	0	26	0	20
JOINT_ISP	287	0.254	0	0.436	0	1	0	1
COMPLEXITY_12SD	287	12.516	12	6.764	0	32	0	30
*COMPLEXITY_12SD*CITY_ISP*	287	5.463	0	8.089	0	32	0	28
*COMPLEXITY_12SD*NATIONAL_ISP*	287	3.436	0	5.721	0	26	0	20
*BIG4*COMPLEXITY_12SD*	287	10.495	10	8.015	0	32	0	30
SIZE	287	5.841	5.56	1.699	1.838	10.03	1.838	10.03
FOLLOW	287	1.593	1.609	0.725	0.693	2.89	0.693	2.89
SURPRISE	287	0.068	0.026	0.129	0	0.927	0	0.927
HORIZON	287	5.222	5.32	0.457	3.401	5.875	3.401	5.875
RETVOL	287	0.079	0.055	0.060	0.015	0.355	0.017	0.355
NUMEST	287	2.279	2.197	1.135	0.693	4.71	0.693	4.71
AGE	287	2.226	2.303	0.935	0	3.807	0	3.807
EARNSD	287	0.122	0.054	0.229	0.002	1.708	0.002	1.708
ROA	287	0.887	0.072	6.464	-48.12	24.731	-22.332	24.731
STOCKTURNOVER	287	0.003	0.003	0.002	0	0.01	0	0.01
YE	287	0.864	1	0.343	0	1	0	1

Panel B: Pearson Correlation Analysis

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	*AFE*	1.000																							
2	*DISP*	.256**	1.000																						
3	*COMPLEXITY_6SD*	-.141*	-0.011	1.000																					
4	*COMPLEXITY_12SD*	-0.110	0.040	.866**	1.000																				
5	*Big4*	-0.017	-0.054	0.039	.127*	1.000																			
6	*Big4*COMPLEXITY_6SD*	-.121*	-0.073	.740**	.703**	.625**	1.000																		
7	*BIG4*COMPLEXITY_12SD*	-0.103	-0.077	.643**	.792**	.631**	.922**	1.000																	
8	*CITY_ISP*	-0.058	-0.045	0.088	.136*	.339**	.291**	.300**	1.000																
9	*NATIONAL_ISP*	-0.020	-0.049	0.064	0.104	.347**	.260**	.270**	.506**	1.000															
10	*JOINT_ISP*	-0.038	-0.074	.132*	.164**	.281**	.279**	.286**	.714**	.811**	1.000														
11	*COMPLEXITY_6SD*CITY_ISP*	-0.073	-0.037	.453**	.443**	.303**	.571**	.536**	.822**	.470**	.646**	1.000													
12	*COMPLEXITY_12SD*CITY_ISP*	-0.071	-0.038	.398**	.489**	.299**	.524**	.570**	.827**	.470**	.647**	.957**	1.000												
13	*COMPLEXITY_6SD*NATIONAL_ISP*	-0.049	-0.060	.388**	.381**	.290**	.502**	.473**	.487**	.835**	.750**	.665**	.637**	1.000											
14	*COMPLEXITY_12SD*NATIONAL_ISP*	-0.049	-0.060	.388**	.381**	.290**	.502**	.473**	.487**	.835**	.750**	.665**	.637**	1.000**	1.000										
15	*SIZE*	-.294**	-.202**	.250**	.294**	.229**	.332**	.359**	.191**	.130*	.180**	.265**	.302**	.185**	.185**	1.000									
16	*FOLLOW*	-.241**	0.011	.319**	.385**	.217**	.387**	.413**	.187**	.196**	.209**	.291**	.318**	.269**	.269**	.753**	1.000								
17	*SURPRISE*	.498**	.442**	-.172**	-0.073	0.001	-.154**	-0.099	-0.054	-0.041	-0.054	-0.061	-0.037	-0.029	-0.029	-.239**	-.169**	1.000							
18	*LNHORISON*	-.144*	-0.005	.177**	.164**	0.083	.201**	.175**	0.102	0.055	0.082	.124*	0.113	0.090	0.090	0.095	.265**	-0.098	1.000						
19	*RETVOL*	0.046	0.087	-0.049	-0.085	-0.054	-0.092	-0.115	-0.085	-.127*	-0.083	-0.080	-0.090	-.125*	-.125*	-0.106	-.213**	0.052	-.315**	1.000					
20	*NUMEST*	-.170**	0.071	.265**	.344**	.202**	.335**	.372**	.167**	.165**	.158**	.259**	.294**	.232**	.232**	.724**	.931**	-0.064	.250**	-.192**	1.000				
21	*AGE*	0.008	-0.016	0.057	0.107	.133*	0.101	.140*	.180**	0.089	0.078	.182**	.198**	.124*	.124*	.129*	0.066	-0.053	0.066	-.192**	0.112	1.000			
22	*EARNSD*	.198**	0.069	0.070	.136*	.118*	.134*	.168**	0.115	0.107	.134*	.143*	.183**	.132*	.132*	.202**	.225**	.159**	0.054	0.112	.269**	0.062	1.000		
23	*ROA*	-.143*	-.140*	0.040	0.051	0.015	0.026	0.039	0.058	0.057	0.077	0.022	0.036	0.028	0.028	.151*	0.078	-0.103	-0.047	.155**	0.098	0.109	0.033	1.000	
24	*STOCKTURNOVER*	.128*	0.089	-0.018	0.068	0.104	0.033	0.091	-0.029	0.006	-0.036	-0.009	0.033	-0.017	-0.017	.249**	.328**	.153**	-0.079	-0.005	.364**	-0.068	0.076	-0.060	1

Table 5: Multivariate Tests on Moderating Role of City-Level Industry Specialisation on Forecast Properties Based on Sub-Sample

$$FORECAST\_PROPERTIES = \beta_0 + \beta_1 CITY\_ISP + \beta_2 \text{SIZE} + \beta_3 \text{FOLLOW} + \beta_4 \text{SURPRISE} + \beta_5 \text{HORIZON} + \beta_6 \text{RETVOL} + \beta_7 \text{NUMEST} + \beta_8 \text{AGE} + \beta_9 \text{EARNSD} + \beta_{10} \text{ROA} + \beta_{11} \text{STOCKTURNOVER} + \text{YEAR DUMMIES} + \text{INDUSTRY FIXED EFFECTS} + \varepsilon. \quad (3)$$

Panel A: When the sub-sample is determined based on the aggregate score of six complex standards

VARIABLES	AFE	AFE	DISP	DISP	REVISION	REVISION
	High Complex	Low Complex	High Complex	Low Complex	High Complex	Low Complex
INTERCEPT	0.094	0.093	0.078	0.185	0.035	0.033
	[0.93]	[0.95]	[1.50]	[1.00]	[0.49]	[0.50]
CITY_ISP	**-0.017****	0.012	-0.003	-0.002	-0.008	-0.014
	[-2.14]	[0.83]	[-0.29]	[-0.23]	[-0.43]	[-0.86]
SIZE	-0.008	-0.019***	-0.015*	-0.007	-0.026**	-0.010
	[-1.59]	[-2.84]	[-1.68]	[-1.64]	[-2.08]	[-1.09]
FOLLOW	-0.013	-0.006	-0.001	-0.006	-0.008	-0.008
	[-0.68]	[-0.17]	[-0.06]	[-0.60]	[-0.31]	[-0.22]
SURPRISE	0.317***	0.199**	0.188	0.041	0.315	0.191
	[2.75]	[2.37]	[1.02]	[1.32]	[1.11]	[1.32]
HORIZON	-0.013	-0.005	-0.012	-0.032	-	-
	[-0.70]	[-0.32]	[-0.80]	[-1.01]	-	-
RETVOL	0.078	-0.030	0.182	-0.110	0.270	-0.230
	[1.45]	[-0.29]	[1.33]	[-0.73]	[1.32]	[-0.89]
NUMEST	0.010	0.005	0.017	0.013	0.037	0.009
	[1.09]	[0.23]	[1.09]	[1.47]	[1.46]	[0.45]
AGE	0.008*	0.006	0.003	0.009	0.002	0.010
	[1.96]	[0.77]	[0.98]	[1.38]	[0.30]	[1.02]
EARNSD	-0.018	0.156***	-0.015	0.036	-0.031	0.086
	[-1.31]	[2.93]	[-0.56]	[1.14]	[-0.76]	[1.06]
ROA	-0.003**	-0.001	-0.002	-0.001*	-0.001	0.000
	[-2.48]	[-1.33]	[-1.33]	[-1.80]	[-0.35]	[0.54]
STOCKTURNOVER	2.523	4.875	-0.597	1.509	-2.268	9.476*
	[1.11]	[1.38]	[-0.28]	[1.07]	[-0.50]	[1.77]
YE	-0.014	-0.010	0.011	-0.016	0.035	-0.015
	[-0.94]	[-0.69]	[0.62]	[-0.94]	[1.31]	[-0.54]
INDUSTRY FIXED EFFECTS	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	144	143	129	111	113	101
R-squared	0.66	0.53	0.48	0.48	0.46	0.46
Adj. R-squared	0.55	0.39	0.28	0.26	0.21	0.22

Panel B: When the sub-sample is determined based on the aggregate score of twelve standards

VARIABLES	AFE High Complex	AFE Low Complex	DISP High Complex	DISP Low Complex	REVISION High Complex	REVISION Low Complex
INTERCEPT	0.082	0.835	0.013	0.134	0.068	0.062
	[1.18]	[1.06]	[0.18]	[1.13]	[1.03]	[1.31]
CITY_ISP	**-0.016***	0.033	-0.005	0	-0.005	**-0.019***
	[-1.88]	[0.70]	[-0.40]	[-0.00]	[-0.27]	**[-1.69]**
SIZE	-0.002	-0.045**	-0.009	-0.009**	-0.015	-0.014**
	[-0.27]	[-2.26]	[-1.30]	[-2.18]	[-1.53]	[-2.23]
AGE	0.002	0.058	0	0.007	-0.003	0.009
	[0.55]	[1.57]	[-0.19]	[1.54]	[-0.56]	[1.49]
SURPRISE	0.422***	0.099	0.334***	0.03	0.659***	0.084
	[6.46]	[0.61]	[3.46]	[1.01]	[4.74]	[0.81]
ROA	-0.002*	-0.003*	-0.001	-0.001	0.002	0
	[-1.92]	[-1.82]	[-0.59]	[-1.51]	[1.29]	[1.12]
FOLLOW	-0.021	0.186	-0.001	0	-0.02	-0.015
	[-1.30]	[1.27]	[-0.04]	[0.00]	[-0.62]	[-0.73]
NUMEST	0.005	-0.114	0.01	0.011*	0.036**	0.017
	[0.59]	[-1.47]	[1.21]	[1.68]	[2.21]	[1.45]
RETVOL	-0.107*	-0.335	0.088	0	-0.014	-0.161
	[-1.76]	[-0.85]	[1.06]	[-0.00]	[-0.11]	[-0.77]
EARNSD	0.003	0.922**	-0.022	-0.009	0	-0.038
	[0.16]	[2.21]	[-0.98]	[-0.45]	[0.01]	[-0.91]
HORIZON	-0.004	-0.158	0.003	-0.022	-	-
	[-0.28]	[-1.17]	[0.23]	[-1.11]	-	-
STOCK TURNOVER	1.968	-6.496	-2.445	1.124	-7.399	5.634
	[1.01]	[-0.32]	[-0.75]	[0.86]	[-1.17]	[1.47]
YE	-0.034***	0.034	0	-0.01	0.018	-0.015
	[-2.97]	[0.68]	[-0.02]	[-0.74]	[0.93]	[-0.69]
INDUSTRY FIXED EFFECTS	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	126	161	117	123	103	111
R-squared	0.72	0.4	0.59	0.47	0.64	0.44
Adj. R-squared	0.61	0.23	0.42	0.27	0.45	0.21

See Appendix A for variable definitions. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels respectively (two-tailed test).