Essays on Financial Reporting Quality and Auditor Attributes

Zhuoan Feng

A dissertation submitted in fulfilment of requirements for the degree

of

Doctor of Philosophy (PhD)

Accounting Discipline Group

UTS Business School

University of Technology Sydney

Australia

November 2018

Certificate of Original Authorship

I, Zhuoan Feng declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the UTS Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

Production Note:

Signature: Signature removed prior to publication.

Date: 20 November 2018

Abstract

This dissertation consists of three stand-alone essays in the areas of financial reporting quality and auditor attributes.

The first essay investigates how test power impacts research relevance and uses earnings management research as the case. I argue that the relevance of accounting research outside of academia is often limited because researchers typically place far greater weight on the relative cost of type I versus type II errors. To illustrate the extent of this problem, I examine the performance of a simple financial ratio-type analysis for detecting earnings overstatements when the total misclassification costs are minimised subject to the relative cost of type I versus type II errors. I then contrast the likelihood of type I versus type II errors from this approach with those arising from several widely used measures of unexpected accruals. The results illustrate how commonly-used unexpected accruals measures reduce the type I error rate by sacrificing the type II error rate. Since accounting information users and auditors typically face much higher costs with respect to type II errors, I explicitly identify why unexpected accruals models are likely far less useful in detecting earnings overstatements than a relatively simple approach using financial statement analysis red flags. The results highlight the fundamentally contrasting incentives facing accounting researchers relative to those who might otherwise use the results from empirical research in practice, and serve as a warning when the broader relevance of accounting research is increasingly under question.

The second essay explores whether auditor industry specialisation is associated with the quality of voluntary non-GAAP earnings disclosures. Industry-specialist auditors are expected to influence the measurement and reporting of non-GAAP earnings due to their greater understanding of industry-specific accounting issues. More generally, the role of auditors is expected to extend beyond the narrow GAAP compliance perspective (DeFond et al. 2018). Consistent with this notion, the results show that the exclusions from GAAP earnings (i.e., non-GAAP exclusions) tend to have less predictive ability for future operating earnings when the firm is audited by an industry-specialist auditor, indicating a higher degree of non-GAAP earnings quality. Further, non-GAAP earnings quality is relatively higher in clients from industries where non-GAAP disclosure is more prevalent, since clients from prevalent industries are more likely to have comparable non-GAAP earnings benchmarks which limit their motivations and abilities to report aggressive non-GAAP earnings numbers. Hence, I predict that the role of industry-specialist auditors is more important in industries where non-GAAP disclosures are less prevalent, as the non-GAAP quality is relatively lower among these firms. The results support the prediction, and demonstrate that industry-specialist auditors enhance not only the quality of mandatory disclosures, but also the quality of voluntary disclosures.

The final essay investigates the association between audit partner change and the quality of non-GAAP earnings voluntarily disclosed by firms. The results show that non-GAAP exclusions tend to be more conservative for clients with new audit partners. I also find that the association between audit partner change and non-GAAP earnings quality is more pronounced among client-firms within industries where non-GAAP disclosures are less prevalent. Finally, the results reveal that non-GAAP earnings are more conservative when audit partner change occurs among Big 4 clients and clients with less independent and smaller boards. Overall, the results provide important insights as to the possible consequences of audit partner changes extending to the quality of voluntary disclosures, in addition to the effect on voluntary disclosure of GAAP-compliance information.

Acknowledgement

My journey to completing the PhD dissertation has been profoundly supported by a number of people. First of all, I would like to express my sincere gratitude to Professor Stephen Taylor, who has been a tremendous source of guidance, support and understanding. I have enjoyed a maximum degree of intellectual freedom under his supervision. I am also deeply indebted to Associate Professor Yaowen Shan for having his door open to me at all times and providing comments and advice throughout my PhD program.

I am grateful for the continuous and consistent support from University of Technology Sydney (UTS), which offered me an excellent opportunity to study and allowed me to focus my efforts on the thesis. Special appreciation goes to Professor Martin Bugeja, Professor Jere Francis, Professor Andrew Ferguson and all the staff and colleagues in Accounting Discipline Group, UTS Business School and UTS. Especially, I would like to acknowledge the role of Luke Bayley in helping identify the abnormal sales index measure, and editorial advice from Kerry Davies.

Appreciation is extending to my fellow peers in the PhD program. Special thanks must be given to Alex Tong, Andrew Dymock, Jin Sug Yang, Luiz Fernando Distadio, Ross McClure, Sam Sherry, Subagio Efendi, Thulaisi Sivapalan, and Wei Hu for supplying endless amounts of energy, ideas, laughter and friendship throughout the journey of my PhD.

Finally, my heartfelt thanks go to my parents. I am especially grateful for their love, patience and understanding throughout my PhD candidature.

Table of Contents

List of Tables

Chapter One: Introduction

The three stand-alone essays in this dissertation investigate topics in the areas of financial reporting quality and auditor attributes. The first essay of the thesis responds to a fundamental, namely the relevance of accounting research. The relevance of accounting research beyond the academic community has continuously been questioned. In some countries, broad national assessments of research relevance and/or researchers' engagement with end-users is either already undertaken or proposed. One of the examples is Australia's national research evaluation framework, known as Excellence in Research for Australia (ERA), administered by the Australian Research Council. Hence, I expect that accounting researchers will face increasing pressure to demonstrate how their research impacts well beyond the academy. The purpose of the first essay is to highlight how a fundamental concern for researchers (avoiding type I errors) potentially works against the production of accounting research with broad external relevance. I use the extensive literature directed towards identifying instances of earnings management to demonstrate this dilemma.

More specifically, the first essay argues that the relevance of accounting research outside of academia is often limited because researchers typically place far greater weight on the relative cost of type I versus type II errors. To illustrate the extent of this problem, I examine the performance of a simple financial ratio-type analysis for detecting earnings overstatements when the total misclassification costs are minimised subject to the relative cost of type I versus type II errors. Then, I contrast the likelihood of type I versus type II errors from this approach with those arising from several widely used measures of unexpected accruals. The results illustrate how commonly-used unexpected accruals measures reduce the type I error rate by sacrificing the type II error rate. As accounting information users and auditors typically face much higher costs with respect to type II errors, I explicitly identify why unexpected accruals models are likely far less useful in detecting earnings overstatements than a relatively simple approach using financial statement analysis of red flags. The results highlight the fundamentally contrasting incentives facing accounting researchers relative to those who might otherwise use the results from empirical research in practice, and serve as a warning when the broader relevance of accounting research is increasingly under question.

While the first essay highlights fundamental concerns with the broader relevance of accounting research directed at detecting manipulations of statutory earnings, regulators and external auditors recently have raised increasing concerns about the quality of disclosures beyond the minimum requirements of accounting standards (Black and Christensen 2018). To respond to these concerns, the second and third essays of this dissertation extend the extant analysis of auditor effects to a broader view, namely the quality of voluntary disclosure. The second and third essays investigate the association between auditor attributes and the quality of alternative performance measures voluntarily disclosed by the management (which I label as "non-GAAP earnings"). Since non-GAAP earnings numbers do not comply with accounting standards and are not strictly subject to audit, managers have substantial discretion over their measurement and presentation. In fact, the reporting of non-GAAP earnings metrics has raised considerable regulatory and public concerns regarding the quality of these metrics, because of the increasing prevalence of non-GAAP disclosures and, more importantly, the frequent allegation that disclosed non-GAAP earnings are systematically higher than GAAP earnings (Hoogervorst 2016). Such systematic differences may substantially mislead capital market participants

In the second essay, I examine the association between auditor industry specialisation and the quality of non-GAAP earnings, as a case of voluntary disclosure. Non-GAAP earnings are essentially managerial adjustments of GAAP earnings from audited financial reports, though they are beyond the statutory disclosure requirements. However, auditors' responsibilities extend beyond certifying compliance with accounting standards (DeFond et al. 2018). Since audited financial reports and voluntary disclosures are complementary mechanisms (Ball et al. 2012), industry-specialist auditors can thus assist clients in enhancing the quality of both statutory disclosures and voluntary disclosures such as non-GAAP earnings (DeFond and Zhang 2014). In addition, auditors' legal responsibilities in respect of statutory and non-statutory information, and their frequent use of non-GAAP metrics as a materiality benchmark, also suggest possible channels through which auditor industry specialisation could influence the quality of non-GAAP earnings. Since industry-specialist auditors have greater incentives to provide higher quality audit (DeFond and Zhang 2014), industry-specialist auditors are more likely to assign a higher weight to the consistency between statutory and non-statutory earnings, raise concerns about any material inconsistency with managers and directors, and thus play a more active monitoring role in the reporting of non-GAAP earnings metrics, particularly in cases where aggressive non-GAAP earnings numbers are provided in the auditing process. Consistent with this view, I find that clients of industry-specialist auditors report relatively higher quality non-GAAP earnings, where quality is defined as the level of predictability in items excluded from GAAP earnings (Doyle et al. 2003; Gu and Chen 2004; Kolev et al. 2008; Frankel et al. 2011).

Furthermore, I expect that non-GAAP earnings may potentially be higher quality for firms in industries where non-GAAP earnings disclosures are more prevalent. Firms in industries where such disclosure is relatively more prevalent are more likely to have multiple comparable non-GAAP earnings benchmarks from their industry peers, which limit their ability and motivation to report aggressive non-GAAP earnings numbers (Black et al. 2012; Doyle et al. 2013). In contrast, firms from industries with a limited number of non-GAAP earnings disclosers would be better able to justify and provide relatively aggressive non-GAAP earnings figures without being detected and criticised by the market. Consistent with this perspective, the results suggest that non-GAAP earnings quality are relatively higher in clients from prevalent industries.

Since the quality of non-GAAP earnings varies across to the prevalence of such disclosure, I then examine whether the association between non-GAAP earnings quality and auditor industry specialisation differs between these two groups of industries. Along this line, I find that the effect of industry-specialist auditors is concentrated among client-firms from industries where non-GAAP disclosures are relatively less common. In the absence of comparable non-GAAP earnings benchmarks from industry peers, auditors with industry specialisation may have a greater advantage in identifying material inconsistencies between non-

GAAP and GAAP earnings, thereby enhancing the quality of non-GAAP earnings numbers among those firms (Balsam et al. 2003; Dunn and Mayhew 2004). Collectively, the results from the second essay suggest that industry-specialist auditors are associated with enhanced disclosure quality beyond the minimum requirements of accounting standards.

The third essay examines the relationship between the change of audit partner and non-GAAP earnings quality, and considers whether disclosed non-GAAP earnings become more "conservative" when an audit partner change occurs.[1] Audit partner change is now required in many jurisdictions as a means of enhancing audit independence (Firth et al. 2012). Supporters of audit partner change argue that "long auditor tenure can lead to overfamiliarity with client management and reluctance to resist pressure from the client regarding accounting policy choices" (Stewart et al. 2016, p.181). Audit partner change is seen as a less-costly alternative to audit firm change (Hamilton et al. 2005) while potentially achieving a similar objective of encouraging a fresh approach to the audit. Both regulators and professional bodies believe that greater audit independence should lead to improved audit quality and hence improved financial reporting quality (Fargher et al. 2008; Manry et al. 2008).

In the third essay, I argue that new audit partners prefer conservative accounting choices for both GAAP and non-GAAP earnings, because they are less familiar with their new clients, and have more concerns over potential litigation

[1] In this study, "conservative" non-GAAP earnings refer to a positive association of non-GAAP exclusions and future incomes, suggesting recurring gains are included in non-GAAP exclusions. In contrast, "aggressive" non-GAAP earnings refer to a negative association between non-GAAP exclusions and future incomes, implying the inclusion of recurring expenses among non-GAAP exclusions.

and reputational costs (Kim et al. 2003). Accordingly, new audit partners are more likely to identify cases where non-GAAP earnings numbers are aggressive, particularly when they rely on non-GAAP earnings metrics to set the materiality benchmark. While auditors do not comment publicly on non-GAAP information, they report to the audit committee on whether the non-GAAP information is consistent with the audited financial statements (Black and Christensen 2018). Thus, I predict that new audit partners are more likely to raise concerns regarding the consistency and quality of non-GAAP earnings metrics and discuss them with managers, the audit committees and the boards. Managers, on the other hand, may consider this action as a form of threat and pressure (Turley and Zaman 2007). In equilibrium, managers are expected to be less likely to disclose aggressive non-GAAP earnings because of greater pressure from new audit partners. Consistent with the notion, I find that non-GAAP exclusions contain more recurring gains rather than recurring expenses when clients have new audit partners, suggesting that non-GAAP earnings numbers are more conservative.

Similar to the second essay, I also find that the quality of non-GAAP earnings is relatively higher in firms from industries where non-GAAP disclosure is more prevalent. Also, I find that the positive association between audit partner change and non-GAAP earnings conservatism is more pronounced in client-firms from industries where non-GAAP disclosure is less prevalent. Moreover, I find that the impact of audit partner change on non-GAAP earnings quality is more significant among Big 4 clients and those with weaker corporate governance environments as represented by lower board independence and smaller board size.

Overall, the results of the third essay demonstrate that audit partner change leads to more conservative voluntary financial reporting.

In summary, each of these three stand-alone essays responds to long-debated fundamental concerns in accounting research. Hence, this dissertation makes several contributions to the academic literature. First, it contributes to the extent of earnings management literature, especially at the practical level, by comparing the performance of the financial ratio-type analysis and commonly used unexpected accruals measures in detecting earnings overstatements when the total misclassification costs are minimised. Further, it contributes to the auditing literature and the voluntary disclosure literature by examining the impact of auditor attributes on the quality of non-statutory (i.e., voluntary) earnings disclosures. Overall, this dissertation enhances our understanding of the practical limitation of a large body of so-called "earnings management" research, as well as offering new insights into how external auditors influence overall disclosure quality beyond compliance with accounting standards.

Although the second and third essays are connected, each essay in the thesis is structured as a separate research paper. As such, each chapter begins with an introduction and includes sections on hypothesis development (or motivation), data, methods, results, robustness checks and conclusions. This structure has resulted in some duplication of the hypothesis development in Chapters Three and Four. Most tables are inserted into the chapters where appropriate, with the development of abnormal sales index measures (Chapter Two) and some detailed information about auditing standards (Chapter Three and Four) consigned to the appendices.

Chapter Two: How Test Power Impacts Research Relevance: The Case of Earnings Management Research

2.1 Introduction

The relevance of accounting research beyond the academic community has frequently been questioned. In some countries, broad national assessments of research relevance and/or researchers' engagement with end-users is either already underway, or proposed.[2] Hence, I expect that accounting researchers will face increasing pressure to provide evidence that their research has an impact beyond the academy. The purpose of this chapter is to highlight how a fundamental concern among researchers (avoiding type I errors) potentially works against the production of accounting research with broad external relevance. I use the extensive literature directed towards identifying instances of earnings management to illustrate this dilemma.

Critics focus on several reasons they believe accounting research has limited relevance outside of academia. While some focus on the choice of research questions (Kaplan 2011; Dyckman and Zeff 2015), others argue that there are significant barriers to the successful transmission of knowledge created by academic research to end users (Hoang et al. 2017). Still, others argue that the relevance of research is limited by researchers' obsession with "statistical significance" (Ohlson 2015). While these are all important considerations, I argue that a fundamental restriction on the broader relevance of accounting research

[2] For example, in the United Kingdom the Research Assessment Exercise includes an explicit requirement to provide evidence of impact (typically in the form of case studies). A similar assessment is scheduled for Australian universities in 2018, which will be an extension of the periodic assessment of research quality known as Excellence in Research for Australia (ERA).

arises from the extremely high weighting given by researchers to the costs of type I errors (i.e., falsely rejecting the null hypothesis). My argument is consistent with Hopwood (2007), who criticises the "cautious" approach of accounting researchers, and argues that social science journals generally (including accounting) are more concerned with ensuring the methodological and statistical validity of the results than the novelty or broader applicability of the research.[3]

I argue that this "cautiousness" reflects researchers' overriding concern with type I errors, namely minimising the probability of falsely rejecting the null hypothesis. One example is the development of methods used to detect earnings management. The detection of accounting manipulation is surely a topic of considerable practical interest to regulators, auditors, and investors (Fields et al. 2001). In highlighting the potential impact of accounting research on practice, an American Accounting Association committee specifically cites the extensive literature addressing the identification of earnings management and tests of its causes and consequences (Moehrle et al. 2009). However, it is amazing to consider the near total absence of evidence suggesting that this research has had a significant influence on practice.[4] Likewise, Ball (2013) argues that the absence of regulatory or prosecutorial action based on this type of evidence suggests that it had little external relevance. This study is motivated by this same concern.

Despite early evidence that the Jones (1991) method for measuring abnormal accruals lacks sufficient statistical power to detect earnings management

---

[3] Hopwood (2007) argues that, in this respect, social sciences compare unfavourably to the natural sciences.

[4] Although Moehrle et al. (2009) cite earnings management research as an example of accounting research with professional impact, they do not specific examples or citations of the use of this research in practice.

of "plausible magnitude" (Dechow et al. 1995), a plethora of papers identify various causes and consequences of earnings management (Dechow et al. 2010). This research has widespread and long-standing currency in top-tier accounting journals, and these journals continue to publish incremental refinements in the methods used for this purpose (Collins et al. 2017; Owens et al. 2017). Innovations to models used to estimate unexpected accruals are largely confined to methodological modifications controlling for firm performance (Kothari et al. 2005), non-linear growth (Collins et al. 2017) and the match between accruals and cash flows from operations (Dechow and Dichev 2002; McNichols 2002).[5] It is striking that the evidence offered for innovations almost universally focuses on a reduction in type I errors. These studies pay virtually no attention to explicitly improving the power of these models.[6]

Why are accounting researchers so concerned with type I errors? Given the near-absence of top-tier publications that provide evidence of an absence of earnings management behaviour (i.e., which conclude that the null is true), it would seem obvious that researchers face strong incentives to detect results that reject the null hypothesis.[7] Hence, there is natural concern that this type of research may reflect a bias toward rejecting the null, and referees and editors take

[5] For example, Dechow et al. (1995) outline several possible extensions to the Jones model. Kothari et al. (2005) subsequently recommend this approach be implemented via a performance-matched control sample. Most recently, Collins et al. (2017) propose further refinements to Jones-type models that deal with non-linear growth and performance effects.
[6] A notable exception is Dechow et al. (2012), who focus on improved power to detect earnings management when the expected reversal effect is included in the model of expected accruals. However, while they document substantial power improvement, their method requires ex ante specification of the reversal period, which Gerakos (2012) identifies as both theoretically difficult and impossible to implement in real-time surveillance settings.
[7] A possible exception arises when examining alleged effects of regulatory intervention, or even the extent to which an effect used as the basis for justifying regulatory intervention is actually evident. Examples include the effects on accounting quality of the provision of non-audit services

great care to avoid the publication of papers that are subsequently found to reflect a type I error. One way researchers address this concern is by using methods which are recognised to be most appropriate for reducing the likelihood of type I errors.

However, at the practical level, regulators, auditors, and accounting information users are likely far more concerned with the power of methods to detect earnings management (type II errors) than they are with wrongly concluding that some firms have engaged in earnings management (type I errors). In fact, I expect that most practical concerns about earnings management revolve around the overstatement of earnings, and those concerned are far more concerned with minimising the costs of type II errors. An obvious example is the auditing profession. It is extremely rare to find an auditor subject to litigation resulting from the understatement of earnings; just as regulatory actions are similarly rare. For example, investors rarely sue auditors over earnings understatements, except where the resulting firm undervaluation has a direct economic cost, such as in a management buyout of external stockholders. On the other hand, the cost of an auditor's failure to recognise a material earnings overstatement is severe. This is especially true when compared with the costs of additional analysis which ultimately suggests that the "problem" is either minor or otherwise simply not present. These type I errors likely have a very low cost relative to a type II error. In short, the practical costs of type II errors are significantly higher than those associated with type I errors.[8]

[8] The relative costs of type I and type II errors have been examined in previous research (Beneish 1999; Dechow et al.2011).

The Figure 1 shows the 2x2 diagram of type I and type II errors.

Figure 1: Type I and Type II errors

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">The truth</td></tr>
<tr><td>Non-Manipulator</td><td>Manipulator</td></tr>
<tr><td rowspan="2">Auditor’s detection</td><td>Non-Manipulator</td><td>Correctly classified</td><td>False negative (Type II error)</td></tr>
<tr><td>Manipulator</td><td>False positive (Type I error)</td><td>Correctly classified</td></tr>
</table>

Put simply, the research community and the potential users of the research in practice face fundamentally different incentives with regard to the minimisation of total expected error costs. This problem is especially evident when considering the earnings management literature and its (non)relevance to practice. Given the trade-off between type I and type II errors (Sheskin 2003), modification of unexpected accruals models improves model specification and reduces type I errors at the expense of increasing type II errors. For example, Kothari et al.’s (2005) performance-matched approach is effective in mitigating type I errors that arise from the association between the accrual model residual and firms’ performance. However, the performance-matched approach based on *ROA* detects upward earnings management equivalent to 1%, 2% and 4% of assets, at a rate of 12.8%, 26.8%, and 60.0% respectively.[9] This rate is substantially lower than the rate reported by Kothari et al. (2005) for the modified Jones model, which detects these positive unexpected accruals at a rate of 21.2%, 38.0%, and 88.4%

[9] To put these figures in perspective, note that for the Compustat population as a whole, net income divided by total assets is around 4%. Hence, unexpected accruals equal to 4% of total assets is actually equivalent to total income, on average. Such massive earnings management would surely be self-evident.

respectively.[10] Perhaps ironically, both sets of results reinforce Dechow et al.'s (1995) conclusion that unexpected accruals models "lack power in detecting earnings management of plausible magnitudes".

I contrast the power of a simple financial ratio-type analysis for identifying instances of significant earnings overstatements, with an analysis based on several widely-used measures of unexpected accruals. I develop a measure based on simple accruals, supplemented by several red flag variables derived from financial statement analysis techniques. Importantly, this study considers the relative cost of type I and type II errors, and conducts a direct comparison between my earnings management measure and unexpected accruals measures when the total expected misclassification costs of type I and type II errors are minimised. The approach in this study is intended to highlight just how important the relative costs of these errors are in determining the practical usefulness of the different approaches to identifying earnings overstatements.

The primary concern in this chapter is not the development of an improved, let alone novel method for detecting earnings overstatements. Beneish (1999) provides evidence regarding the detection of a small sample of GAAP violations disclosed in Accounting and Auditing Enforcement Releases (AAERs) using red flag variables. Likewise, others found evidence suggesting that a broad selection of financial ratios can detect earnings management. For example, Dechow et al. (2011) develop an F-score model based on accruals quality, financial performance, non-financial performance, off-balance-sheet activates, and market-related variables. The F-score model correctly classifies about 64% of their sample firms

[10] See Kothari et al.'s (2005) Table 4.

in detecting earnings overstatements with an average type I and type II error rates of 36% and 32% respectively. While Dechow et al. (2011) (Figure 2) illustrate how the trade-off between type I and type II errors can be considered by accounting information users, they do not directly compare the detection power of their F-score with "standard" unexpected accruals measures, let alone conduct a comparison when the total misclassification costs are minimised. Jansen et al. (2012) propose a new diagnostic for earnings overstatements based on discretionary changes in a firm's profit margin and asset turnover ratio. However, the resulting measure is only able to correctly classify about 20% of earnings overstatements, implying a type II error rate of 80%. Moreover, they do not compare the power of their new diagnostic for identifying earnings overstatements with unexpected accruals measures. Nor do they consider the relative costs of type I and type II errors.

In contrast to these studies, the fundamental concern of this research is the trade-off between type I and type II errors, as highlighted by the extent to which my simple measure based on ratio analysis outperforms various unexpected accrual models when the total misclassification cost is minimised. Relative to unexpected accrual models that have been a mainstay of financial accounting research, I provide evidence on the superiority of using simple red flags based on financial statement analysis for detecting earnings overstatements when realistic trade-offs between the costs of type I and type II errors are considered, and the misclassification cost is minimized by identifying the optimal cut-off point.

I calibrate the model based on a comparison of firms subject to AAERs identifying earnings overstatements and a set of control firms. I expect that firms subject to AAERs reflect a very high likelihood of relatively substantial earnings overstatement (Dechow et al. 1995, 1996b; Dechow et al. 2011).[11] Indeed, the AAERs typically reflect earnings manipulation outside the boundaries of GAAP (Christen et al. 2017). I calibrate a model that distinguishes between AAER cases and a set of control firms, which is also relatively robust to a plausible range of assumed values for the cost of type I and type II errors. In particular, I first match each upward earnings manipulator with five control firms, selected based on industry membership, firm size, and time-period. Then, I estimate the model using a logistic regression of the indicator of AAERs on accruals and a set of red flag variables including changes in sales, the divergence between accruals and cash flows, inventory changes, changes in bad debts reserves and changes in asset quality. My analysis is therefore focused on indicators that I expect to reflect attempts to manage earnings beyond the boundaries of GAAP, particularly those that result in the overstatement of earnings. Finally, I use the predicted probability derived from the EM-score model as the EM-score for each observation.

I then conduct the EM-score classification analysis based on the optimal cut-off point, namely the cut-off EM-score. The cut-off EM-score is determined by identifying where the total expected misclassification costs are minimised, namely the sum of the costs associated with type I and type II errors. For this purpose, I assume the prior probability of fraudulent financial reporting is in the

[11] However, despite being instances of relatively extreme earnings management, the extent of the accounting manipulation does not appear to be fully anticipated prior to the announcement of SEC action (Feroz et al. 1991; Dechow et al. 1996b; Dechow et al. 2012; Files 2012).

1-4% range, and assume the relative cost of type I and type II errors ranges from 10:1 to 50:1. The expected cost of misclassification is a function of the prior probability of fraudulent financial accounting, the prior probability of non-fraudulent financial accounting, the observed type I and type II error rates, and the relative cost of type I and type II errors.

Following the identification of optimal scores, I then similarly examine the power of several commonly-used unexpected accrual measures using the same sample of AAER firm-years. The unexpected accrual measures I consider include the modified Jones model (Dechow et al. 1995), the modified Dechow and Dichev (2002) approach suggested by McNichols (2002) (hereafter modified DD model) and the performance-matched model based on *ROA* (Kothari et al. 2005). To compare the power of the EM-score model with these unexpected accruals measures, I first compare their marginal effects for identifying earnings overstatements using logistic regressions. The marginal analysis indicates that, in general, the power of my model is about five times that of typical unexpected accruals, or a simple total accruals measure.

Subsequently, I choose the cut-off point for unexpected accruals when the total expected misclassification costs are minimised. I thus directly compare the power of unexpected accruals measures to my model. I find that, when the misclassification costs are minimised, unexpected accruals measures can correctly classify on average 90% of the sample with a type I error of 7% and type II error of 84%. Most importantly, the results provide a consistent pattern whereby the high overall accuracy of unexpected accruals models primarily reflects a significantly lower rate of type I errors. In contrast, unexpected accruals are only able to separate the most extreme examples of manipulation, such that the type II error rate for the unexpected accruals measures typically exceeds 75%, while those for my model are consistently around 25% or less. These results, therefore, are consistent with the notion that commonly-used unexpected accruals measures reduce the type I error rate at the expense of increased type II errors. Importantly, I also find that the unexpected accrual measures do not perform significantly better than a simple measure of total accruals.

Overall, the results are consistent with the view that academic research directed at detecting earnings management using extensions of the Jones (1991) model gives insufficient weight to the issue of greatest practical concern, namely the power of these methods to detect substantial earnings overstatements. While the focus of researchers on minimising type I errors is entirely understandable given their relatively high cost to the researchers, reviewers and editors concerned, my results also highlight a fundamental tension between the academic "rigour" of this research and its practical relevance. Although Dechow et al. (1995) clearly identify that the Jones (1991) model lacks power, researchers have continued to place far greater weight on their results and those subsequent researchers (e.g., Kothari et al. 2005), addressing how type I errors can be minimised.

This study makes two important contributions. First, the approach I take stands in stark contrast to recent attempts at further enhancing extant measures of unexpected accruals, either by the addition of further explanatory variables (Dechow and Dichev 2002; McNichols 2002; Collins et al. 2017) or via the use of matching procedures (Kothari et al. 2005). In many respects, my approach is closer in spirit to studies that have concentrated on a specific accrual adjustment.[12] Unlike many prior studies that examine firms subject to AAERs, my concern is with the power of methods used to identify earnings manipulation, rather than the causes or consequences (Dechow et al. 1996b; Beneish 1999; Dechow et al. 2011). The results in this study highlight how the assumed cost of type I versus type II errors substantially impacts how such research is conducted, and particularly the relevance of the research beyond the academy.

Second, this study contributes to the extent earnings management literature, especially at the practical level, by directly comparing the performance of my model and other commonly used unexpected accruals models. In contrast to prior research, I compare the performance of these measures after explicitly considering the relative cost of type I and type II errors and hence, the need to minimise overall misclassification costs. The results indicate that, when misclassification costs are minimised, unexpected accruals models reduce type I error rates at the expense of type II errors. Since accounting information users and auditors likely face drastically higher costs associated with type II errors relative to type I errors, unexpected accruals models are inevitably far less useful than a simple financial statement analysis approach.

[12] Examples where a single accrual adjustment is examined include Miller and Skinner (1998), Marquardt and Wiedman (2004), Petroni (1992) and Beaver and McNichols (1998). Relatedly, Bowen et al. (2002) and Davis (2002) examine the use of grossed-up revenue and barter, and Rasmussen (2013) examines the implications of revenue recognition methods for earnings management and earnings informativeness, but only for a specific group of firms (i.e., internet firms or the semiconductor industry).

The remainder of this chapter proceeds as follows. Section 2.2 describes the estimation of the EM-score, while the results of the attempt to distinguish between AAER and control firms using the EM-score are summarised in section 2.3. In section 2.4, I consider the relative ability of several unexpected accrual measures to distinguish between the same two groups of firms. Section 2.5 discusses additional tests for the robustness check, while section 2.6 concludes.

2.2 EM-score estimation

The essence of the approach to identifying instances of earnings overstatements is to supplement a simple measure of operating accruals with some relatively straightforward financial ratio-type analysis. I next discuss the motivation and the selection of the financial ratio-type variables that I hypothesise to be associated with upward earnings manipulations. Each financial ratio-type variable can be viewed as a red flag, with the overall result of an earnings management score (which I call the "EM-score"). The variables employed in the model include a selection of financial statement ratios directed at the detection of either premature revenue recognition or increased cost deferral. These variables are commonly used in practice (Melumad and Nissim 2009). I choose these variables based on a trade-off between comprehensiveness and my primary interest being to highlight the relative lack of power for detecting earnings overstatements of accruals-based measures used to identify earnings management.[13] Most financial ratios are

[13] I have also considered the financial ratio variables used by Beneish (1999) and Dechow et al. (2011), and chosen the variables that are most commonly used in practice and which have significant differences between upward earnings manipulators and non-manipulators.

constructed so as to identify time series variation consistent with the financial statement effects of earnings overstatements.

However, time series changes do not provide indication of the absolute level of aggression or the significance of past distortions. To the extent that past distortions are significant, manipulation may be better detected by comparing differences in the magnitudes of certain financial statement ratios relative to comparable firms. In many cases, however, peer firm differences in financial statement ratios are an unreliable indicator of manipulation, often-reflecting firm and industry-specific factors. Accordingly, the five financial ratio-type variables which I combine with operating accruals to form a model to predict the likelihood of earnings overstatements (i.e., to form an EM-score) all capture the time series change from the year before the accounting fraud (i.e., the most recent 10-K filing) to the first year of GAAP violation.[14] Briefly, the five financial ratio type variables and the accruals variable which I consider are as follows:

Operating accrual magnitude (ACC): *ACC* is the value of operating (i.e., net working capital) accruals deflated by total assets in the year of a GAAP violation. I measure operating accruals as net income before extraordinary items plus depreciation and amortisation expense less cash flow from operations. I expect higher values of *ACC* to be associated with a greater likelihood of earnings overstatement.

I compute *Sales index (SLSI)*: *SLSI* as the ratio of reported net revenue relative to a notional estimate of unmanipulated net revenue. Stubben (2010) finds

[14] See the notes to Table 2 for an abbreviated definition of each variable.

that revenue models are less biased, better specified, and more powerful than commonly used accrual models. To estimate unmanipulated net revenue, I examine the time series change in the ratio of accounts receivable to net revenue. As detailed in Appendix 2.1, the estimate for unmanipulated net revenue assumes that all times series changes in the value of this ratio are the result of manipulation, and measures its effect accordingly. I assume a *SLSI* value in excess of one reflects aggression (or an increase in aggression) in the firm's revenue recognition policy.

Accruals index (ACCI): practitioners often identify a divergence between earnings and cash flow as a prime indicator of earnings manipulation (Schilit 2010). I measure *ACCI* as one plus the current value of operating accruals deflated by the average of current and lagged total assets in the year of GAAP violation, divided by one plus the lagged value of operating accruals scaled by the aforementioned deflator (the average of total assets for the year of GAAP violation and the prior year). This index captures the time series change in the magnitude of total accruals. A value in excess of one reflects a growing divergence between operating earnings and cash flows.

Inventory index (INVI): Management has considerable discretion with respect to the timing of inventory write-offs. Production decisions can also be used to inflate inventory levels and thereby decrease the associated cost of goods sold expense. Several studies find evidence highlighting the possible role of inventory accounting techniques as methods to manipulate reported earnings (Summers and Sweeney 1998; Marquardt and Wiedman 2004; Roychowdhury

2006; Zang 2011). I measure *INVI* as one plus the ratio of current inventory to net revenue, all deflated by one plus the ratio of lagged inventory to lagged net revenue. I expect an index value in excess of one to be associated with a greater probability of upwards earnings manipulation.

Reserve index (RESI): Considerable subjectivity is involved in the estimation of expense provisions. Audit partners surveyed by Nelson et al. (2002) report that "cookie jar reserves" are the most popular method for manipulating reported earnings. Marquardt and Wiedman (2004) and Teoh et al. (1998) report context-specific results consistent with this claim. Accordingly, *RESI* measures the relation between the reserve for bad debts receivables and the current accounts receivables balance. I measure *RESI* as one plus the ratio of the lagged value of the bad debts reserve relative to the lagged receivables balance, all deflated by one plus the ratio of the current bad debts reserve relative to the current receivables balance. A value in excess of one is consistent with earnings manipulation.[15]

Asset quality index (AQI): An increase in so-called soft asset balances may be indicative of aggressive cost capitalisation. Beneish (1999) highlights the significance of soft assets in an analysis of SEC Enforcement Releases. In addition, Dechow et al. (2011) find that, when firms have more soft assets on their balance sheet, there is more discretion for management to change assumptions to meet short-term earnings goals.

[15] Of course, there are many other types of provisions that could be used to manipulate earnings, such as reserves for future health care benefits, and periodic maintenance reserves. However, these require more context-specific analysis than the relatively generalist red flag approach.

I define *AQI* as one plus the current value of soft assets deflated by the average of the current and lagged value of total assets in the year of GAAP violation, divided by one plus the lagged value of soft assets scaled by the aforementioned deflator (the average value of total assets for the year of GAAP violation and the prior year). Soft assets include the Compustat items "other current assets", "other non-current assets" and intangibles. Goodwill is excluded from intangibles to remove the distorting effects of merger and acquisition activity. An *AQI* in excess of one may indicate increased cost deferral and a resulting upward manipulation of earnings.

Table 2.1 lists the definition and measurement for all variables.

Table 2.1 Variable Measurement

Variable	Measurement
Panel A: Earnings management variables	
EM	*EM* is the indicator variable equals to one, if the firm is listed in the AAER as the upwards earnings manipulators, otherwise zero.
EM-Score	*EM-Score* is the predicted probability that is derived from the EM-Score model (EXP(*EM*)/(1+Exp(*EM*)) and deflated by the unconditional probability of earnings overstatements.
EM-Score_indicator	*EM-Score_indicator* equals to one if the *EM-score* is equal to or greater than 1.00, otherwise zero.
Panel B: Red flag variables	
ACC	The operating accruals magnitude is measured by $(EBEI_t+D\&A_t-CFO_t)/Assets_t$, where *EBEI* is earnings before Extraordinary Items; *D&A* refers to the aggregate Depreciation and Amortisation Expense; *Assets* refer to the total value to all assets.
SLSI	The sales index is measured by ***Net Revenue$_t$/ Net Revenue†***, where *Net Revenue* is the net sale of the firm. *Net Revenue*† is the estimated value of non-manipulated net revenue (see Appendix 2.1).
ACCI	The accruals index is measured as one plus the current value of operating accruals deflated by the average of current and lagged total assets in the year of GAAP violation: $\frac{1+((EBEI_t + D\&A_t - CFO_t)/((Assets_t + Assets_{t-1})/2))}{1+((EBEI_{t-1} + D\&A_{t-1} - CFO_{t-1})/((Assets_t + Assets_{t-1})/2))}$
INVI	The inventory index is measured as one plus the ratio of current inventory to net revenue, all deflated by one plus the ratio of lagged inventory to lagged net revenue: $\frac{1+(Inventory_t / Cost\ of\ Goods\ Sold_t)}{1+(Inventory_{t-1} / Cost\ of\ Goods\ Sold_{t-1})}$
RESI	The reserve index is measured as one plus the ratio of the lagged value of the bad debts reserve relative to the lagged receivables balance, all deflated by one plus the ratio of the current bad debts reserve relative to the current receivables balance: $\frac{1+(BDR_{t-1}/Receivables_{t-1})}{1+(BDR_t/Receivables_t)}$, where *BDR* is the provision for doubtful receivables
AQI	The asset quality index is measured as one plus the current value of soft assets deflated by the average of the current and lagged value of total assets in the year of GAAP violation, divided by one plus the lagged value of soft assets scalded by the aforementioned deflator (the average value of total assets for the year of GAAP violation and the prior year): $\frac{1+(SA_t/((Assets_t + Assets_{t-1})/2))}{1+(SA_{t-1}/((Assets_t + Assets_{t-1})/2))}$, where *SA* is the soft assets measured as the sum of *Other Current Assets*, plus Intangibles, and *Other Non-Current Assets*.

Table 2.1 (continued)

Variable	Measurement
Panel C: Performance indicators variables	
RECD_RECT	The ratio of *Receivables* to *Sales*
INV_COGS	The ratio of *Inventory* to *Cost of Goods Sold*.
SA_AT	The ratio of *Soft Assets* to *Total Assets*. *Soft Assets* are defined as the sum of *Other Current Assets*, plus *Intangibles*, and *Other Non-Current Assets*.
SG	The growth rate(%) in reported *Net Revenue* from the control year to the fraud year
ASSET_GR	The growth rate (%) of *Total Assets*
ASSETTURN	The asset turnover is measured as *Net Revenue* divided by *Total Assets*.
ROA	The return on assets is measured as *Earnings before Extraordinary Items* deflated by *Total Assets*.
GM	The gross margin is computed as *Gross Profit* divided by *Net Revenue*.
SGA	The margin for Selling, General and Administrative Expenses (*SGA*) is computed as the ratio of *SGA* expenses divided by *Net Revenue*.

2.3 EM-score evidence

Upward earnings manipulators are identified from the SEC's AAERs. Although not all AAERs pertain to fraudulent financial reporting, they are the best place to find a fairly complete sample of SEC actions concerning violations of GAAP. AAERs have been previously used to identify samples where earnings manipulation can be reasonably assumed (Feroz et al. 1991; Dechow et al. 1995; Beneish 1999; Dechow et al. 2011; Schrand and Zechman 2012). I obtain the AAERs dataset from the University of California, Berkeley in 2015. The dataset, dated at 21/10/2014, includes 1,554 AAERs listed on the SEC website between 1989 and 2011. Forty-three non-financial companies were identified as having understated a prior 10-K filing.[16] I exclude observations that have insufficient Compustat data. The final sample yielded 573 earnings manipulators that have overstated their earnings. Each sample firm is then matched with five control firms, selected based on industry membership (two-digit SIC code), firm size (measured in total assets), and time-period (year of GAAP violation). I require control firms to have sufficient data on Compustat. Panel A of Table 2.2 provides a summary of the sample selection procedure, while Panel B reports summary statistics for key variables of 573 earnings manipulators and 2,865 control firms used in this research.

[16] The dataset includes AAERs observations up to 2011. I end in 2011 because the SEC needs to average three years to identify and investigate the alleged GAAP violations.

Table 2.2 Sample Selection Criteria and Summary Statistics

Panel A: Sample selection criteria

AAERs obtained from the SEC website that are dated between 1989 and 2011	1,554
Less: Earnings Manipulators identified as understated from the AAER search	(43)
Less: Earnings Manipulators with insufficient data on Compustat	(938)
Final Sample	573

Panel B: Summary Statistics

	N	Mean	Std	Q1	Median	Q3
ACC	3424	-0.019	0.154	-0.039	-0.005	0.032
SLSI	3424	0.027	0.099	0.000	0.003	0.014
INVI	3424	1.000	0.066	0.985	1.000	1.010
RESI	3424	1.004	0.054	0.992	1.000	1.009
AQI	3424	1.032	0.105	0.994	1.005	1.036

Table 2.2 reports the summary of sample selection criteria and the summary statistics of key variables used in my paper. *ACC* is the operating accruals magnitude, *SLSI* is the sales index, *ACCI* is the accruals index, *INVI* is the inventory index, *RESI* is the reserve index, and *AQI* is the asset quality index. All variables have been winsorized at percentile bands one and ninety-nine. All variables are defined in Table 2.1.

I use logit analysis to model the differential financial statement characteristics observed between the two sample cohorts (earnings manipulators and control firms). I calculate the earnings management score (EM score) as:

$$EM = W_1X_1 + W_2X_2 + \ldots\ldots + W_jX_j \tag{1}$$

where *EM* is the indicator of earnings manipulators, equals one if the firm is an earnings manipulator listed in AAER, zero otherwise; *X* is the j^{th} attribute or independent variable (red flag accounting ratios); *W* is the estimated coefficient or weight for the j^{th} attribute.

I estimate a logit model with the dependent variable equal to one if the observation is an earnings manipulator, or zero otherwise. The independent variables are the red flag ratios identified previously. I subsequently use the predicted probabilities derived from the EM-score model (Exp(EM)/(1+Exp(EM)) and scale to the unconditional probability to evaluate several cut-off values to determine how well the variables employed in the model distinguish financial statement distortions resulting from earnings management.

Univariate statistics

Table 2.3 reports univariate test for AAERs firms and control firms. Panel A of Table 2.3 compares the six red flag accounting ratios and firm's performance indicators estimated in the year of GAAP violation (fraud year) and the previous year (control year) between earnings manipulators and non-manipulators. The results of the univariate test in Panel A suggest that earnings manipulators have significantly higher *ACC* (t = 3.29), *SLSI* (t = 4.65), *ACCI* (t = 3.02) and *AQI* (t = 4.00) than non-manipulators in the fraud year. In the control year, all these red flag ratios, except *ACCI*, are still significantly higher in earnings manipulators, compared with non-manipulators. However, the difference in differences tests only indicate a significant difference in *SLSI* (t = 1.87). On the other hand, in Panel B, I am unable to find any significant difference between earnings manipulators and non-manipulators in other performance indicators. These results suggest that the red flag accounting ratios have better predictability to detect the earnings overstatements, compared with other performance indicators.

Table 2.3 Univariate test – AAERs and Control Firms

	Manipulators		Non-manipulators		Manipulator vs. non-Manipulators		
	Control Year	**Fraud Year**	**Control Year**	**Fraud Year**	**Control Year**	**Fraud Year**	**Difference in difference**
Panel A: The red flag accounting ratio							
ACC	0.009	0.010	-0.012	-0.022	**0.021****	**0.032*****	0.014
					(2.24)	(3.29)	(1.33)
SLSI	0.069	0.056	0.025	0.026	**0.044*****	**0.030*****	**0.014***
					（5.86）	（4.65）	(1.87)
ACCI	1.015	1.043	1.015	1.003	0.000	**0.040*****	0.015
					（0.01）	（3.02）	(0.97)
INVI	0.995	1.005	1.002	0.999	-0.007	0.006	0.004
					(-1.30)	(1.43)	(0.80)
RESI	1.001	1.007	1.002	1.004	-0.001	0.003	-0.000
					(-0.32)	(0.88)	(-0.09)
AQI	1.062	1.055	1.029	1.028	**0.033*****	**0.027*****	0.004
					(4.32)	(4.00)	(0.51)
Panel B: Performance indicators							
RECD_RECT	0.058	0.064	0.063	0.065	-0.005	-0.001	0.002
					(-0.62)	(-0.20)	(0.22)
INV_COGS	0.221	0.226	0.208	0.202	0.013	0.024	0.015
					(0.66)	(1.47)	(0.74)
SA_AT	0.175	0.197	0.180	0.187	-0.005	0.010	-0.012
					(-0.37)	(0.86)	(-0.86)
SG	0.666	0.431	0.351	0.378	0.315	0.053	0.032
					(1.53)	(0.20)	(0.12)
ASSET_GR	0.683	0.647	0.543	0.476	0.140	0.171	0.149
					(0.45)	(0.60)	(0.48)
ASSETTURN	1.245	1.111	1.183	1.168	0.062	-0.057	0.062
					(0.91)	(-0.91)	(0.88)
ROA	-0.009	-0.038	0.000	-0.021	-0.009	-0.017	0.006
					(-0.60)	(-1.03)	(0.33)
GM	0.367	0.387	0.375	0.369	-0.008	0.018	-0.002
					(-0.41)	(1.07)	(-0.12)
SGA	0.357	0.366	0.327	0.346	0.030	0.020	0.016
					(0.93)	(0.68)	(0.47)

The two-sample t-test is used to examine the differences in the mean value of financial statement characteristics between earnings manipulators and non-earnings manipulators in their *control* and *fraud* years. *Fraud* year refers to the year of GAAP violation (10-K filing) under investigation. *Control* refers to the year prior to the 10-K filing under SEC investigation.

For the red flag accounting ratios, *ACC* is the operating accruals magnitude, *SLSI* is the sales index, *ACCI* is the accruals index, *INVI* is the inventory index, *RESI* is the reserve index, and *AQI* is the asset quality index.

For the Control and Fraud year, *RECD_RECT* is the ratio of account receivables to sales, *INV_COGS* is the ratio of inventory to cost of goods sold, *SA_AT* is the ratio of soft assets to total assets, *SG* is the sales growth rate, *ASSET_GR* is the growth rate of total assets, *ASSETTURN* is the assets turnover, *ROA* is return on assets, *GM* is the gross margin, and *SGA* is the margin for selling, general and administrative expenses. All variables have been winsorized at percentile bands one and ninety-nine. The t-stats are reported in brackets directly beneath each coefficient and test statistic. *** (**, *) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 2.1.

EM-score validity

Table 2.4 extends the analysis to examine average values for each of the EM-score components between certain EM-score ranges. The frequency distribution indicates that most upward earnings manipulators have high EM-scores. For the most part, higher EM-score values are associated with increases in each of the six red flag accounting ratios. However, the *ACC*, *SLSI*, and *ACCI* variables provide the most contribution. This is particularly the case for higher EM-scores. Overall, the results presented in Table 2.4 indicate that each of the red flag variables contributes to increased EM-scores. In addition, the results highlight the usefulness of the EM-score model as a screening tool with practical relevance.

Table 2.4 Analysis of Red Flag Ratios for Various EM-score Values

EM-score Range			*FREQ*	*FREQ (Manipulator)*	*FREQ (non-Manipulator)*	*ACC*	*SLSI*	*ACCI*	*INVI*	*RESI*	*AQI*
0.125	<=EM-Score<	0.15	4	0	4	-1.309	0.003	0.504	0.992	0.883	0.877
0.15	<=EM-Score<	0.175	3	0	3	-1.333	0.002	0.328	1.000	1.083	0.772
0.175	<=EM-Score<	0.2	3	0	3	-1.238	0.004	0.448	0.883	1.075	0.772
0.2	<=EM-Score<	0.225	2	2	0	-1.145	0.000	0.531	1.025	1.088	0.783
0.225	<=EM-Score<	0.25	1	0	1	-1.379	0.000	0.118	1.014	1.306	0.772
0.25	<=EM-Score<	0.275	1	0	1	-1.379	0.458	-0.215	0.994	1.018	0.947
0.275	<=EM-Score<	0.3	5	0	5	-1.100	0.042	0.036	1.052	1.103	0.868
0.3	<=EM-Score<	0.325	4	0	4	-0.799	0.006	0.205	0.968	0.980	0.839
0.325	<=EM-Score<	0.35	2	1	1	-0.727	0.002	0.377	1.066	0.955	0.884
0.35	<=EM-Score<	0.375	1	1	0	-1.259	0.003	0.248	0.717	1.381	0.914
0.375	<=EM-Score<	0.4	3	1	2	-0.512	0.005	1.207	1.061	0.982	0.829
0.4	<=EM-Score<	0.425	4	0	4	-0.944	0.058	0.280	0.977	1.174	0.938
0.425	<=EM-Score<	0.45	4	1	3	-0.421	0.005	0.832	0.985	0.996	0.785
0.45	<=EM-Score<	0.475	4	1	3	-0.604	0.027	0.628	0.993	1.093	0.854
0.475	<=EM-Score<	0.5	3	1	2	-0.518	0.060	0.753	0.872	1.038	0.880
0.5	<=EM-Score<	0.525	4	0	4	-0.366	0.011	0.948	0.997	0.969	0.888
0.525	<=EM-Score<	0.55	5	1	4	-0.533	0.015	0.703	0.982	1.104	0.898
0.55	<=EM-Score<	0.575	6	0	6	-0.485	0.056	0.688	0.917	0.993	0.989
0.575	<=EM-Score<	0.6	11	0	11	-0.424	0.012	0.649	0.928	1.015	0.959
0.6	<=EM-Score<	0.625	12	0	12	-0.302	0.025	0.911	0.990	0.943	0.984
0.625	<=EM-Score<	0.65	13	0	13	-0.171	0.032	1.213	0.975	0.911	0.956
0.65	<=EM-Score<	0.675	23	1	22	-0.205	0.022	0.889	0.946	0.931	0.965
0.675	<=EM-Score<	0.7	15	4	11	-0.217	0.024	0.921	0.961	1.007	0.926
0.7	<=EM-Score<	0.725	29	4	25	-0.222	0.029	0.907	0.970	1.011	0.949
0.725	<=EM-Score<	0.75	36	5	31	-0.148	0.014	1.046	0.996	0.986	0.953
0.75	<=EM-Score<	0.775	41	6	35	-0.144	0.025	1.004	0.969	0.997	0.955
0.775	<=EM-Score<	0.8	40	7	33	-0.162	0.017	0.886	0.994	1.004	0.978
0.8	<=EM-Score<	0.825	57	2	55	-0.079	0.010	1.009	0.995	0.988	0.964
0.825	<=EM-Score<	0.85	72	12	60	-0.084	0.025	0.988	1.002	0.985	0.988
0.85	<=EM-Score<	0.875	137	13	124	-0.063	0.013	0.952	0.994	0.987	0.989
0.875	<=EM-Score<	0.9	168	25	143	-0.047	0.012	0.994	0.988	0.994	0.995
0.9	<=EM-Score<	0.925	329	40	289	-0.026	0.008	0.996	0.991	0.997	0.997
0.925	<=EM-Score<	0.95	431	69	362	-0.017	0.010	0.992	0.998	1.001	1.004
0.95	<=EM-Score<	0.975	404	46	358	0.002	0.014	1.005	0.994	0.999	1.010
0.975	<=EM-Score<	1	312	60	252	0.015	0.013	1.021	1.002	1.001	1.018
1	<=EM-Score<	1.025	235	40	195	0.024	0.025	1.007	1.011	1.005	1.019
1.025	<=EM-Score<	1.05	887	198	689	0.057	0.040	1.052	1.009	1.014	1.079
1.05	<=EM-Score<	1.075	123	31	92	0.045	0.200	1.086	1.026	1.053	1.364
1.075	<=EM-Score<	1.1	2	1	1	0.151	0.496	0.309	1.043	0.993	1.534

Table 2.4 reports mean values for the six red flag accounting ratios for non-financial firm-year observations within certain EM-score ranges. *ACC* is the operating accruals magnitude, *SLSI* is the sales index, *ACCI* is the accruals index, *INVI* is the inventory index, *RESI* is the reserve index, and *AQI* is the asset quality index. All variables have been winsorised at two standard deviation points from the mean. The column *FREQ* measures the frequency of observations within certain EM-score ranges. All variables are defined in Table 2.1.

EM-score calibration

Table 2.5 reports univariate and multivariate estimations of the relation between the EM-score components and the likelihood of an earnings overstatement. Univariate logistic regressions are reported as models 1 through 6. As expected, all coefficient estimates are positive. The univariate coefficients and logistic regression statistics for the *ACC* (coefficient = 1.265, t = 3.24) and *AQI* (coefficient = 1.684, t = 4.38) models are significant at the 1% level, while the coefficient on *SLSI* (coefficient = 0.749, t = 1.92) is significant at the 10% level. However, the estimated coefficients for the *ACCI*, *INVI* and *RESI* variables are insignificant.

Multivariate logistic regressions are presented as models 7 through 11 of Table 2.5. Model 7 only includes the *ACC* and *SLSI* variables. I find that only the coefficient on *ACC* (coefficient = 1.200, t = 3.11) is significantly associated with the indicator variable of earnings overstatements. Additional variables are added to the logistic regression in models 8 through to 11. I find that *ACC* outperforms other red flag variables in detecting earnings overstatements, while *SLSI* and *RESI* have marginal power in identifying earning manipulators. Finally, I include all the six red flag variables in the model 11. I find coefficients on *ACC* (coefficient = 1.344, t = 2.84), *RESI* (coefficient = 1.649, t = 1.91) and *AQI* (coefficient = 1.523, t = 3.84) are significantly positive. These results suggest that the operating accrual magnitude (*ACC*), the relation between the reserve for bad debts receivables and the current receivables balance (*RESI*) and the soft assets balance (*AQI*) have the most power for detecting earnings overstatements.

Table 2.5 Results of the EM-score Models

	Variables Employed In the Logit Model							
	INT	*ACC*	*SLSI*	*ACCI*	*INVI*	*RESI*	*AQI*	Pseudo R^2
Model 1	-1.596*** (-34.75)	**1.265***** (3.24)	-	-	-	-	-	0.0040
Model 2	-1.631*** (-34.31)	-	**0.749*** (1.92)	-	-	-	-	0.0011
Model 3	-1.918*** (-8.67)	-	-	0.307 (1.44)	-	-	-	0.0007
Model 4	-2.210*** (-3.21)	-	-	-	0.601 (0.88)	-	-	0.0002
Model 5	-2.562*** (-3.11)	-	-	-	-	0.949 (1.16)	-	0.0004
Model 6	-3.356*** (-8.31)	-	-	-	-	-	**1.684***** (4.38)	0.0058
Model 7	-1.615*** (-33.89)	**1.200***** (3.11)	0.628 (1.60)	-	-	-	-	0.0048
Model 8	-1.383*** (-4.87)	**1.402***** (3.05)	**0.666*** (1.68)	-0.229 (-0.83)	-	-	-	0.0050
Model 9	-1.594** (-2.12)	**1.386***** (3.00)	**0.660*** (1.67)	-0.230 (-0.83)	0.212 (0.30)	-	-	0.0051
Model 10	-3.300*** (-2.85)	**1.492***** (3.21)	0.644 (1.62)	-0.191 (-0.69)	0.200 (0.29)	**1.673*** (1.93)	-	0.0062
Model 11	-4.643*** (-3.83)	**1.344***** (2.84)	0.585 (1.46)	-0.153 (-0.54)	-0.054 (-0.08)	**1.649*** (1.91)	**1.523***** (3.84)	0.0107

Table 2.5 presents the results of the Logit analysis. *ACC*, *SLSI*, *ACCI*, *INVI*, *RESI* and *AQI* are the individual 'red flag' forensic accounting variables used to distinguish between the group of 573 earnings manipulators and the 2,865 control firms. These variables are outlined in the notes to Table 2. The t-stats are reported in brackets directly beneath each logit coefficient and test statistic. *** (**, *) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 2.1.

Classification accuracy of the red flag accounting ratios

As the next step in considering how well the proposed EM-score approach discerns manipulative from non-manipulative financial reporting, the classification accuracy derived from the predicted probabilities of the EM-score model are analysed according to several optimal cut-off points. The cut-off probability estimate used to measure classification accuracy is determined by finding the point where the expected misclassification costs are minimised. Misclassification costs encompass type I and type II errors. Type I errors occur where the EM-score falsely classifies a company as a manipulator. Type II errors refer to the failure to distinguish earnings manipulators from non-earnings manipulators. As I have already argued, the costs associated with these two error types are likely to differ very substantially in practice. The optimal EM-score to measure classification accuracy is the point where the expected misclassification costs are minimised.

$$EC = q_1(M_{12}/N_1)C_1 + q_2(M_{21}/N_2)C_2 \tag{2}$$

where EC is the expected costs of misclassification; q_1 is the prior probability of fraudulent financial accounting; q_2 is the prior probability of non-fraudulent financial accounting; M_{12}/N_1 is observed type I errors relative to the sample of non-earnings manipulators; M_{21}/N_2 is observed type II errors relative to the sample of earnings manipulators; C_1 is the cost of type I errors; C_2 is the cost of type II errors.

Equation (2) requires estimates for the prior probabilities of fraudulent and non-fraudulent financial reporting. However, it is difficult to measure the true proportion of firms that manipulate earnings beyond the levels permissible by GAAP. Even a sample comprising all AAER firms would not be an exhaustive list of all GAAP violators. The SEC is resource constrained, and is unable to screen all financial reporting activity. Further, identifying the precise line that distinguishes fraudulent financial reporting from an aggressive (but legitimate) application of GAAP is also difficult.

To be consistent with past empirical research, the prior probability of fraudulent financial reporting is arbitrarily estimated to be in the 1-4% range. The estimated cost of type II errors relative to type I errors is also guided by extant empirical analysis. Beneish (1999) estimates relative error costs from a portfolio perspective, and documents a negative 40% return in the quarter containing the discovery of earnings manipulation. Beneish (1999) uses this as an estimate of the cost resulting from the failure to detect fraudulent financial accounting (type II errors) and compares it to the 1-2% average stock return earned by listed firms (type I errors). Utilising these approximations, Beneish (1999) estimates the cost of type II errors to be 20-40 times greater than type I errors.[17]

[17] Of course, this approach measures relative misclassification costs from a shareholder perspective. Other decision makers (such as lenders) may have different objective functions and therefore would assign quite different estimates of relative error costs. However, to take the auditor example in the introduction, the cost of a type II error is expected to be far larger than for a type I error.

Table 2.6 Classification Accuracy of the EM-score Model

RELATIVE COSTS OF TYPE I AND TYPE II ERRORS	PRIOR PROBABILITY OF MANIPULATED EARNINGS	PRIOR PROBABILITY OF NON-MANIPULATED EARNINGS	CUT-OFF EM-SCORE	ACCURACY (%)	TYPE II ERRORS (%)	TYPE I ERRORS (%)
10/1	0.01	0.99	0.9999	43.53	21.00	56.83
20/1	0.01	0.99	0.9999	43.53	21.00	56.83
30/1	0.01	0.99	0.9999	43.53	21.00	56.83
40/1	0.01	0.99	0.9999	43.53	21.00	56.83
50/1	0.01	0.99	0.9999	43.53	21.00	56.83
10/1	0.02	0.98	0.9459	48.75	25.00	51.79
20/1	0.02	0.98	0.9459	48.75	25.00	51.79
30/1	0.02	0.98	0.9459	48.75	25.00	51.79
40/1	0.02	0.98	0.9459	48.75	25.00	51.79
50/1	0.02	0.98	0.9459	48.75	25.00	51.79
10/1	0.03	0.97	0.9345	44.69	22.67	56.32
20/1	0.03	0.97	0.9347	44.73	22.67	56.28
30/1	0.03	0.97	0.9399	45.91	23.67	55.03
40/1	0.03	0.97	0.9399	45.91	23.67	55.03
50/1	0.03	0.97	0.9399	45.91	23.67	55.03
10/1	0.04	0.96	0.9422	42.67	23.75	58.73
20/1	0.04	0.96	0.9422	42.67	23.75	58.73
30/1	0.04	0.96	0.9479	43.94	25.00	57.35
40/1	0.04	0.96	0.9479	43.94	25.00	57.35
50/1	0.04	0.96	0.9479	43.94	25.00	57.35

Table 2.6 investigates the classification accuracy of the EM-Score Model. Accuracy is measured as the percentage of sample firms correctly classified. Type I errors are the misclassification of non-earnings manipulators as earnings manipulators (expressed as a percentage). Type II errors are the misclassification of earnings manipulators as non-earnings manipulators (expressed as a percentage). The prior probability of manipulated earnings refers to the proportion of firms, relative to all firms, that are expected to manipulate earnings beyond the levels permissible by GAAP. The prior probability of non-manipulated earnings is one minus the prior probability of manipulated earnings. The cut-off EM-score is the EM-score associated with the lowest statistical cost of misclassification.

Table 2.6 presents the results of estimating the EM-score associated with the lowest statistical cost of misclassification. It is apparent that this score is easily affected by choice of prior probability estimates and the relative error costs of misclassifications. This is particularly the case for high probability estimates of manipulative reporting. Following Beneish (1999), I estimate the relative cost of type I and type II errors is ranging from 10:1 to 50:1. The probability of upward earnings manipulators from the sample is set from 1% to 4%. Relatively, the probability of non-manipulators is from 99% to 96%. Overall, the results suggest that the EM-score model correctly classifies about 45% of all sample observations with about 25% type II errors and approximate 55% type I errors. This suggests that although the model has some ability to distinguish between sample cohorts, it does so with significant classification error.

2.4 Analysis of unexpected accruals

I benchmark the power of the EM-score approach with several unexpected accrual measures. I use three methods for estimating expected accruals listed in Dechow et al. (2010). The first method is the modified cross-sectional Jones (1991) model suggested by Dechow et al. (1995). I estimate this model as follows:

$$Total\ Accruals_{it} = \alpha + \beta_1(\Delta REV_{it} - \Delta REC_{it}) + \beta_2(PPE_{it}) + \varepsilon_{it} \quad (3)$$

where *Total Accruals* is the difference between income before extraordinary items and operating cash flows, all deflated by the lagged value of total assets. ΔREV is the change in net revenue divided by the lagged value of total assets. ΔREC is the change in accounts receivables deflated by the lagged value of total assets, and *PPE* is the current value of total property, plant and equipment divided by the lagged value of total assets.

The second method for estimating unexpected accruals uses the modified version of the Dechow and Dichev (2002) model as suggested by McNichols (2002). Unexpected accruals are estimated as:

$$Current\ Accruals_{it} = \alpha + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_t + \beta_4 \Delta Sales + \beta_5 (PPE_{it}) + \varepsilon_{it} \tag{4}$$

where Δ*Sales* is computed as the difference between the one period lagged value of *Sales* and the current period of *Sales*, all deflated by total assets and scaled by 100.

The third approach to estimate unexpected accruals is the modified Jones model matched on *ROA*, following Kothari et al. (2005):

$$DisAcc_t - Matched\ firm's\ DisAcc_t \tag{5}$$

Equations (3) through (5) are each estimated in industry cross-section, based on two-digit SIC code and calendar year. Following Dechow et al. (2003), a minimum of ten observations are required. I exclude eleven earnings manipulators due to the additional data requirements, while three earnings manipulators were excluded from the sample due to an insufficient number of two-digit SIC industry year peer firm observations to compute a valid expected accrual model.

The summary statistics of unexpected accruals measures for AAERs and control firms are reported in Panel A of Table 2.7. The summary statistics indicate that the average unexpected accruals calculated by the modified Jones model, the modified DD model, the modified Jones model matching on *ROA* and the total accruals measure are 0.014, 0.006, -0.006 and -0.058 respectively. Panel B compares these measures between earnings manipulators and non-manipulations. Univariate tests suggest that unexpected accruals are significantly higher in manipulators than non-manipulators. For example, the two-sample *t*-test suggests that the average unexpected accruals of manipulators measured by the modified Jones model, the modified DD model and the modified Jones model matching on *ROA* are significantly higher than those from non-manipulators (t = 5.92, 5.99 and 4.05 respectively). Tests of differences in medians reported in Panel C consistently indicate that the median values of unexpected accruals are typically higher for manipulators than non-manipulators (χ^2 = 14.55, 9.90 and 17.53 respectively). Consistent with the results reported by Dechow et al. (2011), these results provide some evidence of the ability of the unexpected accrual measures to distinguish earnings attributes consistent with aggressive financial reporting.

Table 2.7 Summary Statistics and Univariate Test for Unexpected Accruals

Panel A: Summary Statistics of Accruals Measures for AAER and control firms

	N	Mean	Std	Q1	Median	Q3
Unexpected Total Accruals: Modified Jones Model	3342	0.014	0.124	-0.032	0.019	0.068
Unexpected Current Accruals: Modified DD Model	3100	0.006	0.074	-0.026	0.003	0.032
Unexpected Total Accruals: Modified Jones Model matching on ROA	3342	-0.006	0.154	-0.076	-0.004	0.067
Total Accruals	3382	-0.058	0.137	-0.106	-0.050	-0.007

Panel B: *t*-test

	Manipulators	**Non-manipulators**	**Difference: Mean**	***t*-statistic**
Unexpected Total Accruals: Modified Jones	0.043	0.009	0.034	5.92
Unexpected Current Accruals: Modified DD	0.024	0.002	0.022	5.99
Unexpected Total Accruals: Modified Jones matching on ROA	0.019	-0.010	0.029	4.05

Panel C: Median test

	Manipulators	**Non-manipulators**	**Difference: Median**	χ^2
Unexpected Total Accruals: Modified Jones	0.034	0.016	0.018	14.55
Unexpected Current Accruals: Modified DD	0.011	0.001	0.010	9.90
Unexpected Total Accruals: Modified Jones matching on ROA	0.014	-0.009	0.023	17.53

Table 2.7 reports univariate tests for unexpected accrual metrics (UA), as well as tests of the difference between the 562 available firm-year observations identified as earnings manipulators relative to the 2,810 matched non-earnings manipulators. All accrual metrics have been winsorised at percentile bands one and ninety-nine.

Since the results suggest both EM-score and unexpected accruals models have the ability to identify instances of earnings manipulation, a natural question is whether the EM-score outperforms unexpected accruals. Thus, I regress the indicator variable of earnings overstatements on the *EM-score_indicator* and each unexpected accruals measure. The *EM-score_indicator* equals one if the EM-score is equal to or greater than 1.00, otherwise zero.

Results in Panel A of Table 2.8 report that the coefficients on unexpected accruals calculated by the modified Jones model, the modified DD model, and the modified Jones model matching on *ROA* are 1.703, 3.075, and 0.829 respectively. All of these coefficients associated with the unexpected accruals measures are significant at 1% levels. Similarly, the *EM-score_indicator* is also positively and significantly associated with the presence of an earnings overstatement.

Since the results suggest that the unexpected accruals models have some power to detect earnings manipulators, I subsequently conduct a battery of tests to distinguish the power of the EM-score model from the unexpected accruals models. First, I examine the marginal effects based on the logistic regressions. Marginal effects measure the expected instantaneous change in the dependent variable as a function of a change in a certain explanatory variable, while keeping all the other covariates constant.

I first calculate the discrete change of the indicator variable of earnings overstatements from 0 to 1 (*dy/dx*) for the *EM-score_indicator* and each unexpected accruals measure. I then compute the difference between the lower quartile (37.5 percentile) and the upper quartile (75 percentile) for the *EM-*

score_indicator and each unexpected accruals measures. I choose the 37.5 percentile and the 75 percentile because the distribution of the *EM-score_indicator* is concentrated in this range. Finally, I multiply *dy/dx* by the difference between the lower and upper quartiles, and label it as the percentage of increase (*poi*), indicating the variation from 0 to 1 of the earnings overstatement indicator, when the variable of interest moves from its lower quartile value to its upper quartile value.

The results in Panel B of Table 2.8 suggest that the EM-score model has significantly greater power to detect instances of earnings overstatements than unexpected accruals, and simple total accruals. In particular, the power of the EM-score model (*poi* = 5.72%) is about four times higher than for the modified Jones model (*poi* = 1.63%). Similarly, the EM-score model (*poi* = 5.00%) is more than three times better than the modified DD model (*poi* = 1.73%), and six times stronger than the modified Jones model matching on *ROA* (*poi* = 1.15%). For comparison, I also benchmark the power of the EM-score model against the total accruals model, and find that the EM-score model (*poi* = 6.60%) is about six times better than the total accruals model (*poi* = 0.78%).

Table 2.8 Unexpected Accruals as an Identifier of AAERS

Panel A: Multivariate analysis

VARIABLES	(1) *EM*	(2) *EM*	(3) *EM*	(4) *EM*
EM-score_indicator	**0.407*****	**0.370*****	**0.491*****	**0.377*****
	(4.02)	(3.50)	(5.05)	(3.71)
Unexpected Total Accruals: Modified Jones Model	**1.703*****	-	-	-
	(4.11)			
Unexpected Current Accruals: Modified DD Model	-	**3.075*****	-	-
		(4.50)		
Unexpected Total Accruals: Modified Jones Model matching on ROA	-	-	**0.829*****	-
			(2.69)	
Total Accruals	-	-	-	**1.729*****
				(4.61)
Constant	-1.824***	-1.855***	-1.817***	-1.682***
	(-28.95)	(-28.05)	(-28.71)	(-24.42)
Pseudo R^2	0.0173	0.0174	0.0138	0.0185
Observations	3,342	3,100	3,342	3,382

Panel B: Marginal effects using the interquartile range

	Percentage of increase			
EM-score_indicator	5.72%	5.00%	6.98%	6.60%
Unexpected Total Accruals: Modified Jones	2.31%	-	-	-
Unexpected Current Accruals: Modified DD	-	2.34%	-	-
Unexpected Total Accruals: Modified Jones matching on ROA	-	-	1.60%	-
Total Accruals	-	-	-	1.16%

Panel C: Marginal effects using 37.5th to 75th percentiles

	Percentage of increase			
EM-score_indicator	5.72%	5.00%	6.98%	6.60%
Unexpected Total Accruals: Modified Jones	1.63%	-	-	-
Unexpected Current Accruals: Modified DD	-	1.73%	-	-
Unexpected Total Accruals: Modified Jones matching on ROA	-	-	1.15%	-
Total Accruals	-	-	-	0.78%

Three different unexpected accrual estimations are used to distinguish between a group of 562 earnings manipulators and 2,810 control matched non-earnings manipulators. *EM-score_indicator* equals to 1 if the EM-score is equal to or greater than 1, 0 otherwise. All accrual estimates have been winsorized at percentile bands one and ninety-nine. The t-stat is reported in brackets directly beneath each logistic coefficient and test statistic. *** (**, *) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 2.1.

In the second test, I assess the accuracy of unexpected accruals models by using the same approach as in Table 2.6. First, I estimate the 2% and 4% prior probability for manipulated earnings for every unexpected accruals model. I then identify the cut-off point for each model that is associated with the lowest overall cost of misclassification.

The results in Table 2.9 reveal that the modified DD model has the highest total accuracy rate among unexpected accruals measures. Its total accuracy rate consistently exceeds 90%, while the modified Jones model and the modified Jones model matching on *ROA* have total accuracy rates between 80% and 90%. Comparing the type II error rates, the modified Jones model outperforms other unexpected accruals measures, except when the relative cost of type I and type II errors are 40:1 and 50:1, and where the prior probability of manipulated earnings is 4%.

Overall, the results in Table 2.9 present a consistent pattern. Although all unexpected accrual models have high total accuracy rates, this is largely attributable to the low type I error rates (i.e., the range is from 1.38% to 16.18%). However, the trade-off is that unexpected accrual models have high type II error rates (i.e., the range is from 75.50% to 97.50% type II errors). It is also noteworthy that unexpected accrual measures do not significantly outperform the total accruals measure in detecting earnings overstatements. For example, the overall accuracy rate of the simple total accruals measure ranges from 91.44% to 94.03%, while the modified Jones model has accuracy ranging from 85.68% to

94.65%. These results are also consistent with the evidence provided by Dechow et al. (1995) that the Jones model lacks power.

The results in Table 2.9 are consistent with researchers focusing on reduction, so far as possible, of the likelihood of making type I errors via the identification and use of "improved" methods for identifying unexpected accruals. In comparison with the EM-score model, the type I error rates from unexpected accruals measures are significantly lower. The type I error rates from the EM-score model range between 51.79% and 58.73%, while type I error rates from unexpected accruals measures range from 1.38% to 16.18%. The higher type I error rates from the EM–score model leads to the relatively lower total accuracy rates, compared with unexpected accruals measures.

However, it is equally clear that unexpected accruals models reduce type I error rates by sacrificing the type II error rate. For instance, for the modified Jones model, type II errors range from 75.50% to 93.25%, while the highest type II error rate from the EM score model is only 25%. As unexpected, accruals measures are associated with a far higher level of type II errors in detecting earnings overstatements. The results in Table 2.9 support the perspective that unexpected accruals models of the type that dominate earnings management research are not that useful in practical settings, where the failure to identify instances of earnings overstatements has a far higher cost than wrongly concluding that an overstatement has occurred.

Table 2.9 Classification Accuracy of Unexpected Accruals

Panel A: Unexpected Total Accruals: Modified Jones Model

RELATIVE COSTS OF TYPE I AND TYPE II ERRORS	PRIOR PROBABILITY OF MANIPULATED EARNINGS	PRIOR PROBABILITY OF NON-MANIPULATED EARNINGS	CUT-OFF POINT	ACCURACY (%)	TYPE II ERRORS (%)	TYPE I ERRORS (%)
10/1	0.02	0.98	0.1112	87.21	75.50	11.51
20/1	0.02	0.98	0.1112	87.21	75.50	11.51
30/1	0.02	0.98	0.1112	87.21	75.50	11.51
40/1	0.02	0.98	0.1112	87.21	75.50	11.51
50/1	0.02	0.98	0.1112	87.21	75.50	11.51
10/1	0.04	0.96	0.1118	85.68	79.50	11.60
20/1	0.04	0.96	0.1118	85.68	79.50	11.60
30/1	0.04	0.96	0.1192	86.61	80.50	10.59
40/1	0.04	0.96	0.3151	94.65	93.25	1.69
50/1	0.04	0.96	0.3151	94.65	93.25	1.69
Panel B: Unexpected Current Accruals: Modified DD Model						
10/1	0.02	0.98	0.1116	93.48	85.00	4.92
20/1	0.02	0.98	0.1116	93.48	85.00	4.92
30/1	0.02	0.98	0.1116	93.48	85.00	4.92
40/1	0.02	0.98	0.1116	93.48	85.00	4.92
50/1	0.02	0.98	0.1116	93.48	85.00	4.92
10/1	0.04	0.96	0.1116	91.85	87.75	4.83
20/1	0.04	0.96	0.1116	91.85	87.75	4.83
30/1	0.04	0.96	0.1181	92.17	88.25	4.48
40/1	0.04	0.96	0.1121	92.17	88.25	4.48
50/1	0.04	0.96	0.1151	92.17	88.25	4.48
Panel C: Unexpected Total Accruals: Modified Jones Model matching on ROA						
10/1	0.02	0.98	0.1116	82.55	79.50	16.18
20/1	0.02	0.98	0.1116	82.55	79.50	16.18
30/1	0.02	0.98	0.1116	82.55	79.50	16.18
40/1	0.02	0.98	0.1116	82.55	79.50	16.18
50/1	0.02	0.98	0.1638	88.43	85.00	10.07
10/1	0.04	0.96	0.1117	81.28	79.75	16.18
20/1	0.04	0.96	0.1117	81.28	79.75	16.18
30/1	0.04	0.96	0.3713	93.93	96.00	2.32
40/1	0.04	0.96	0.4411	94.78	97.50	1.38
50/1	0.04	0.96	0.4411	94.78	97.50	1.38
Panel D: Total Accruals						
10/1	0.02	0.98	0.1122	92.62	84.50	5.81
20/1	0.02	0.98	0.1122	92.62	84.50	5.81
30/1	0.02	0.98	0.1122	92.62	84.50	5.81
40/1	0.02	0.98	0.1122	92.62	84.50	5.81
50/1	0.02	0.98	0.1122	92.62	84.50	5.81
10/1	0.04	0.96	0.1116	91.44	86.75	5.30
20/1	0.04	0.96	0.1116	91.44	86.75	5.30
30/1	0.04	0.96	0.1116	91.44	86.75	5.30
40/1	0.04	0.96	0.2146	94.03	91.50	2.41
50/1	0.04	0.96	0.2146	94.03	91.50	2.41

Table 2.9 investigates the classification accuracy of the unexpected accruals models, including Unexpected Total Accruals: Modified Jones Model, Unexpected Current Accruals: Modified DD Model, Unexpected Total Accruals: Modified Jones Model matching on ROA and Total Accruals.

Accuracy is measured as the percentage of sample firms correctly classified. Type I errors are the misclassification of non-earnings manipulators as earnings manipulators (expressed as a percentage). Type II errors are the misclassification of earnings manipulators as non-earnings manipulators (expressed as a percentage). The prior probability of manipulated earnings refers to the proportion of firms, relative to all firms, that are expected to manipulate earnings beyond the levels permissible by GAAP. The prior probability of non-manipulated earnings is one minus the prior probability of manipulated earnings. The cut-off point for unexpected accruals is the level of unexpected accruals associated with the lowest statistical cost of misclassification.

2.5 Additional tests

I perform three additional tests (untabulated) to assess the robustness of results.[18] First, I extend the EM-score model to include three additional measures suggested by Dechow et al. (2011). These are the change in receivables (*ch_rec*), the change in inventory (*ch_inv*), and the change in cash sales (*ch_cs*).[19] However, the results are similar because I find that the indicator for AAERs is still positively associated with *ACC*, *RESI* and *AQI*. The inclusion of these additional measures does not change my conclusion that the simple red flag variables are more powerful in detecting earnings overstatements than measures of unexpected accruals.

Second, I also compare the power of the EM-score model with alternative unexpected accruals measures. I re-estimate unexpected accruals using only current accruals rather than total accruals. The results suggest that the EM-score model is significantly more powerful in detecting earnings overstatements than these alternative unexpected accruals measures. For example, unexpected current accruals calculated by the modified Jones model can correctly classify about 90% of the sample firms, with a type I error of 7% and type II error rate of 81%. Similarly, the type I and type II error rates for the modified DD model and the modified Jones model matching on *ROA* are 4% and 88%, and 11% and 81% respectively. The far higher type II errors rates provide further evidence consistent with my argument that Jones-type models reduce type I errors at the expense of

[18] The tabulated results of the additional tests are available from the authors upon request.
[19] Following Dechow et al. (2011), I calculate *ch_rec* as (ΔAccount Receivable/Average total assets), *ch_inv* as (ΔInventory/Average total assets), *ch_cs* as (Percentage change in cash sales (Sales-ΔAccount Receivable)).

sacrificing type II errors, especially when the total misclassification costs are minimised.

In the third additional test, I set the EM-score equal to 1.00 as the cut-off point, instead of choosing an EM-score that minimises total misclassification costs (i.e., I implement a "naïve" benchmark approach). An EM-score of 1.00 indicates that the firm has the same probability of earnings overstatement as the unconditional expectation, while EM-scores greater than one indicate higher probabilities of earnings overstatement. For comparison, I choose 2% (of total assets) as the naïve cut-off point for unexpected accruals and total accruals measures. Examining the distribution of EM-scores reveals that an EM-score of 1.00 is located around the 60th percentile, and when a cut-off point for unexpected accruals of 0.02 is applied, this also is around the 60th percentile of these distributions.

The results of this "naïve" approach result in the EM-score model correctly classifying about 50% of all observations, with type I error rates of about 50% and type II error rates of 30%. Relative to the results reported in Table 2.6, this result is indicative of how minimising the total misclassification cost is associated with the lowest rate of type II errors. In contrast, the results for measures of unexpected accruals, as well as the simple total accruals measure, continue to have lower type I error rates, but at the cost of higher type II error rates. Hence, even when using a naïve strategy with simple cut-off benchmarks, the EM-score approach significantly outperforms commonly used measures of unexpected accruals.

2.6 Conclusion

The analyses in the essay are motivated by a recognition that academic researchers face increasing pressure to provide evidence with the wider impact (i.e., practical relevance). Yet there is relatively little evidence regarding factors that likely restrict accounting research from having this type of impact. Following Hopwood's (2007) argument, I explicitly recognise that accounting researchers face strong incentives to undertake research that has a low probability of making type I errors (i.e., falsely rejecting the null hypothesis). Incentive stands in marked contrast to potential users of research who often face type II error costs that are far higher than those associated with type I errors.

I illustrate this dilemma by considering the limited relevance of earnings management research for identifying relatively egregious instances of earnings overstatements. Although Moehrle et al. (2009) point to earnings management research as an example of how accounting research has practical relevance, they offer no examples of how it is actually used in practice. In contrast, Ball (2013) argues that there is little evidence of methods used in earnings management research being used in practice. I focus on methods used to estimate the extent of earnings management because they have had widespread application and, despite longstanding recognition of issues associated with a lack of power, leading journals continue to publish extensions of these models which have as their primary focus a further reduction in type I errors (Collins et al. 2017).

In contrast to research examining extensions of the Jones (1991) model of expected accruals that typically focus on the extent to which type I errors are reduced, the focus of this study is on the power of these models relative to a simple red flag, accounting ratio-based model for detecting earnings overstatements of a typically large magnitude. I provide evidence that a combination of a simple measure of accruals combined with some straightforward financial ratio analysis can successfully distinguish between firms alleged to engage in quite serious earnings overstatements, relative to a set of matched control firms. The most important components of the EM-score model are measures of operating accruals and estimated revenue manipulation. This result is not surprising, as I rely on a sample of the firm-year subject to SEC enforcement action due to earnings overstatements as the benchmark indicator of upward earnings management.

However, the primary contribution of this study lies neither in the recognition that financial statement analysis techniques are useful for identifying earnings overstatements, nor suggesting a model that is better than that outlined by Dechow et al. (2011). The focus of this study is on highlighting how low test power becomes critical when the expected relative cost of type I and type II errors are explicitly considered, and the resulting misclassification costs are minimised. Despite early evidence on this point by Dechow et al. (1995), there has been little if any evidence on how power becomes increasingly important when the relative costs of type II errors far exceed those associated with type I errors. Although it is entirely appropriate that researchers are concerned with avoiding type I errors, it is equally apparent that users of financial reports (including auditors) are far more concerned with the need to avoid type II errors. The results provide a consistent pattern that commonly used unexpected accruals models reduce type I errors by sacrificing type II errors. In this respect, advances to methods for detecting earnings management that reflect improvements via reduced type I errors have limited practical relevance.

In conclusion, the results of this study highlight the tension between the search for better-specified methods by which to test hypotheses about the factors giving rise to accounting manipulation (or the consequences of manipulation) versus the practical interest in getting the most powerful tools for identifying instances of earnings overstatements where. Although this tension is not necessarily a bad thing, I argue that it needs to be explicitly recognised and that future research directed at practical solutions for identifying earnings overstatements should have a primary focus on increased power, so as to try and minimise type II errors. While accounting researchers continue to emphasise the minimisation of type I error rates, I expect that broader impact of such research to be severely limited.

Chapter Three: Auditor Industry Specialisation and Non-GAAP Earnings Quality

3.1 Introduction

Earnings and performance measures are generally argued to have important roles in stewardship and valuation (IASB 2018). However, the calculation of earnings complying with Generally Accepted Accounting Principles (GAAP) is a highly regulated process, subject to the application of accounting standards and the influence of auditors. Therefore, managers may voluntarily, but also strategically, disclose additional information besides GAAP earnings to better serve either the stewardship or valuation roles (non-GAAP earnings) (Ribeiro et al. 2018). This essay aims to provide evidence of how auditor industry specialisation relates to the quality of non-GAAP earnings voluntarily disclosed by managers. In particular, this essay examines the association between the presence of industry-specialist auditors and the quality of a firm's non-GAAP earnings.

Non-GAAP earnings figures are typically derived from GAAP earnings by excluding certain items that are presumed to be one-off, non-operating and/or non-cash. However, as non-GAAP earnings numbers do not comply with accounting standards, managers have substantial discretion over their measurement and presentation. In fact, the reporting of non-GAAP earnings metrics has raised considerable regulatory and public concern regarding the quality of these metrics, particularly the observed longstanding pattern that the disclosed non-GAAP earnings are on average higher than GAAP earnings, and may mislead capital market participants.[20] This claim is supported by prior evidence that managers appear to use non-GAAP earnings measures to meet earnings benchmarks (Bhattacharya et al. 2004; Heflin and Hsu 2008; Black and Christensen 2009).[21] As such, regulators have questioned whether auditors should play a more significant role in verifying or even attesting to non-GAAP calculations (Black and Christensen 2018).

While non-GAAP earnings numbers disclosed in annual reports are not strictly subject to audit, auditors are legally responsible for the quality of both statutory and non-statutory information (other than the financial report and the auditor's report thereon) included in an entity's annual report.[22] Auditors' responsibilities are firmly rooted in authoritative auditing standards, accounting standards and regulations, which require not just compliance with accounting standards, but also fair presentation and, hence, compel auditors to consider the economic substance of management's disclosure (DeFond et al. 2018). According

[20] For example, Hans Hoogervorst, the chair of the International Accounting Standards Board (IASB), stated in a speech at the 2016 Annual Conference of the European Accounting Association (EAA) that: "more than 88% of the S&P 500 currently disclose non-GAAP metrics in their earnings release. Of those releases, 82% show increased net income and are clearly designed to present results in a more favourable light. One study showed that the popular metric 'core earnings' was on average 30% higher than GAAP earnings. While these are numbers for the US market, securities regulators in the world of IFRS Standards are also concerned that non-GAAP numbers are getting increasingly detached from reality (Hoogervorst 2016)."
The literature also documents the increasing prevalence of non-GAAP disclosure. For example, Entwistle et al. (2005) show that 77% of the S&P 500 US firms reported non-GAAP earnings figures in 2001, while Bhattacharya et al. (2004) show that from 1998 to 2000 there was a very substantial increase in such non-GAAP disclosures. Similarly, Zhang and Zheng (2011) find the frequency of non-GAAP reporting increased significantly over the period 1998–2001.
[21] Bhattacharya et al. (2004) document that the average GAAP EPS is a net loss of 14.7 cents per share (1998–2000), while the corresponding non-GAAP average for the same set of observations is a net income of 8.5 cents per share. Heflin and Hsu (2008) also document a modest decline in the propensity of non-GAAP earnings to meet or beat analysts' forecasts. Black and Christensen (2009) document that managers frequently exclude items that are not "one-off" in nature, since three of the most frequently-used exclusions are recurring items, namely research and development expenses, depreciation and amortisation, and share-based compensation.
[22] See Section 3.2.2 for more details. The relevant auditing standard in Australia is Auditing Standard ASA 720: The Auditor's Responsibilities Relating to Other Information.

to auditing standards, auditors need to identify any material inconsistency between GAAP and non-GAAP earnings based on their knowledge and the context of audit evidence obtained in the audit. In addition, auditors often use the disclosed non-GAAP earnings numbers as the materiality benchmark (PricewaterhouseCoopers 2011; Eilifsen and Messier Jr 2015; Hallman et al. 2017).[23] Given the importance of non-GAAP metrics in the auditing process, examination of the relationship between auditor industry specialisation and the quality of non-GAAP earnings disclosures is warranted.

Auditor industry specialisation reflects an auditor's expertise to deliver higher quality audits (Craswell et al. 1995). Prior literature on auditor industry specialisation suggests that industry-specialist auditors tend to provide higher quality audits because they invest more in industry-specific information technologies and personnel, and have greater knowledge of industry business and accounting practices (Dopuch and Simunic 1982; Craswell et al. 1995). Accordingly, industry-specialist auditors are expected to have greater competence and better client-specific knowledge in delivering higher quality audit, while competency and client-specific knowledge are vital for auditors to plan audits effectively and to identify relevant audit risks (Knechel and Salterio 2016). In addition, industry-specialist auditors, particularly for those who have brand-name reputation, have higher reputational capital at stake compared with non-specialist auditors. Thus, like all auditor characteristics that capture auditor competencies, industry specialisation also provides auditors with greater incentives to deliver high audit quality (DeFond and Zhang 2014).

[23] The relevant Australian auditing standard is ASA 320: Materiality in Planning and Performing an Audit.

In this study, I examine the association between auditor industry specialisation and the quality of non-GAAP earnings, as a case of voluntary disclosure. Non-GAAP earnings are essentially managerial adjustments of GAAP earnings from audited financial reports, though they are beyond the statutory disclosure requirements. Auditors' responsibilities are not just certifying compliance with accounting standards, but also the assurance of fair presentation (DeFond et al. 2018). Since audited financial reports and voluntary disclosures are complementary mechanisms (Ball et al. 2012), industry-specialist auditors thus can assist clients in enhancing the quality of both statutory disclosures and voluntary disclosures such as non-GAAP earnings (Dunn and Mayhew 2004).

In addition, auditors' legal responsibilities in respect of the statutory and non-statutory information, and their frequent use of non-GAAP metrics as a materiality benchmark, also suggest possible channels through which auditor industry specialisation could influence the quality of non-GAAP earnings. Since industry-specialist auditors have greater incentives to provide higher quality audit (DeFond and Zhang 2014), industry-specialist auditors are more likely to assign higher weight to the consistency between statutory and non-statutory earnings, and raise concerns about any material inconsistency with managers and directors, and thus play a monitoring role in the reporting of non-GAAP earnings metrics, particularly in cases where aggressive non-GAAP earnings numbers are provided in the auditing process and are not in line with the statutory earnings numbers. Therefore, non-GAAP earnings quality is expected to be higher for clients of industry-specialist auditors than for clients of non-specialist auditors.

Following prior studies, I measure the quality of non-GAAP earnings as the predictive ability of non-GAAP exclusions from statutory earnings for future operating performance (Doyle et al. 2003; Gu and Chen 2004; Kolev et al. 2008; Frankel et al. 2011). To warrant their exclusions from statutory earnings, non-GAAP exclusions (measured as the difference between non-GAAP earnings and GAAP earnings) should be transitory, without any predictive power for future performance (Kolev et al. 2008; Hsu and Kross 2011). Thus, "high-quality" non-GAAP exclusions are expected to be transitory, while "low-quality" exclusions tend to be permanent and demonstrate a significant association with future operating performance.

I estimate the implication of non-GAAP exclusions for future operating income by regressing future operating earnings on current non-GAAP earnings and non-GAAP exclusions. Using a sample of 2237 firm-year observations from 2001 to 2014 in Australia and multiple measures of auditor industry specialisation, I find a positive association between auditor industry specialisation and non-GAAP earnings quality. For example, for a non-GAAP discloser audited by a non-specialist auditor, a dollar of non-GAAP exclusions is associated with \$0.13 future expenses. In contrast, when a non-GAAP discloser is a client of an industry-specialist auditor, a dollar of non-GAAP exclusions is associated with \$0.04 of future expenses. Similarly, one dollar of non-GAAP exclusions is associated with \$0.02 expenses in the future among non-GAAP disclosers audited by market leader auditors, compared with a future expense of \$0.13 for those audited by non-market leaders. In other words, non-GAAP exclusions disclosed by clients of industry-specialist auditors have less predictive ability for future expenses, indicating that they tend to disclose higher quality non-GAAP earnings measures. The results are robust to several forms of sensitivity analysis, including controlling for endogenous auditor choice and the effect of non-Big 4 specialist auditors.[24]

Next, I examine whether the quality of non-GAAP earnings varies accordingly to the prevalence of such disclosure across client-firm industries.[25] Given the disclosure of non-GAAP earnings numbers is voluntary and varies substantially across industries and firms, firms from industries where non-GAAP disclosures are prevalent would have more comparable benchmarks of non-GAAP earnings from their industry peers. The availability of comparable benchmarks may limit their ability and motivation to report aggressive non-GAAP earnings numbers, since it increases the chance of being identified by market participants (Black et al. 2012; Doyle et al. 2013). On the other hand, firms from industries with a limited number of non-GAAP earnings disclosers would be better able to justify and provide relatively aggressive non-GAAP earnings figures without being detected and criticised by the market. Thus, I expect that the quality of non-GAAP earnings is higher in firms from industries where non-GAAP disclosure is relatively more prevalent. Consistent with the notion, I find supportive evidence that firms from prevalent industries are more likely to report higher quality non-

[24] The Big 4 auditors are Deloitte, Ernst & Young, KPMG and PricewaterhouseCoopers. Throughout the study, I use Big 4 generically to designate Big 4 and Big 5 auditors, depending on the sample period.

[25] I classify companies into industries based on two-digit GICS codes. Following Coulton et al. (2016), I define non-GAAP prevalent industries are those most likely to present non-GAAP information, including Utilities, Consumer Discretionary, Financial and Industrial Classifications. Accordingly, I label industries, besides the above four industries, as less prevalent industries.

GAAP earnings information than those from industries where non-GAAP disclosure is less common.

Given differences in the quality of non-GAAP earnings disclosures across client-firm industries, I further examine whether the positive association between auditor industry specialisation and non-GAAP earnings quality varies across industries where non-GAAP disclosures are prevalent or less prevalent. In the absence of comparable benchmarks of non-GAAP earnings from industry peers, auditors with industry specialisation may have a greater advantage in identifying material inconsistencies between non-GAAP and GAAP earnings, thereby enhancing the quality of non-GAAP earnings numbers among those firms. Therefore, the role of industry-specialist auditors may be more important in client-firms from industries where non-GAAP disclosure is less common, because of their lower quality of disclosed non-GAAP earnings and the lack of comparable non-GAAP earnings benchmarks. In contrast, industry-specialist auditors may play a less important role in monitoring the quality of non-GAAP earnings for client-firms from prevalent industries, since the non-GAAP quality is relatively high among these firms. Consistent with this expectation, I find a significant and positive association between auditor industry specialisation and non-GAAP earnings quality for client-firms from less prevalent industries, but this association becomes insignificant for client-firms from industries where non-GAAP disclosure is more common.

Finally, I examine whether the positive association between auditor industry specialisation and the quality of non-GAAP reporting varies around the mandatory adoption of International Financial Reporting Standards (IFRS) in 2005. The broad change from Australian GAAP (A-GAAP) to Australian equivalents to IFRS (A-IFRS) accounting standards is sometimes characterised as imposing changes in accounting standards, whereby GAAP-based measures become more volatile and/or an increasing degree of unrealised gains and/or losses are included in the GAAP definition of income. Given the possible impact of IFRS on GAAP-based earnings, I argue that auditors are more likely to use non-GAAP earnings as the materiality benchmark because non-GAAP metrics are less volatile, particularly around the mandatory adoption of IFRS. Accordingly, industry-specialist auditors might pay more attention to the quality of non-GAAP earnings, and the impact of auditor industry specialisation on the quality of non-GAAP would be more significant in the post-IFRS period. Consistent with this expectation, the results show that the association between auditor industry specialisation and non-GAAP earnings quality is stronger in the post-IFRS era.

This research makes two important contributions to the auditing and voluntary disclosure literature. First, I explore how auditor attributes, namely various indicators of auditor industry specialisation, influence the quality of non-GAAP earnings metrics, as a case of voluntary disclosure. Other than documenting an association between auditor industry specialisation and the quality of statutory earnings (Balsam et al. 2003; Lim and Tan 2008; Reichelt and Wang 2010), the importance of the effect from industry-specialist auditors on the disclosures of other information is mostly overlooked, particularly other information voluntarily disclosed by firms such as non-GAAP earnings numbers. An exception is Dunn and Mayhew (2004) who provide evidence that enhanced disclosure, as a form of voluntary disclosure, is influenced by whether the firm is a client of the industry-specialist auditor. This study considers the quality of statutory and voluntary disclosures as a whole, while auditors play a critical role in both forms of disclosures. Importantly, the results stress the significant role played by external auditors in influencing a firm's voluntary disclosure behaviour, particularly when voluntarily disclosed financial information (i.e., non-GAAP earnings) has a directly comparable audited benchmark (i.e., GAAP earnings).

Second, this study differs significantly from prior studies that link auditing attributes with non-GAAP disclosures. Prior studies linking auditing attributes with non-GAAP disclosures include Chen et al. (2012), Black et al. (2014) and Hallman et al. (2017). These studies predominantly examine how firms' non-GAAP disclosure decisions influence auditors' judgement. For example, Chen et al. (2012) examine the association between the magnitude of non-GAAP earnings exclusions, the level of audit fees and the likelihood of auditor resignations, while Black et al. (2014) examine the association between the abnormal audit fees and the likelihood of reporting aggressive non-GAAP earnings. Both Chen et al. (2012) and Black et al. (2014) examine the auditor's perspective on non-GAAP disclosures, measured by the level of audit fees. However, these studies do not explore the role of auditors and their attributes in influencing the quality of non-GAAP earnings disclosures. Relatedly, Hallman et al. (2017) investigate the frequency of auditor reliance on non-GAAP earnings metrics when determining the materiality benchmark, and whether such reliance results in less conservative materiality amounts.

In contrast to prior research, this study considers an entirely different direction, namely how auditors influence firms' disclosure behaviour. This direction is in line with most prior research that focuses on attributes of voluntary audited financial reports. The results of this study provide important insights into how the use of auditors with industry specialisation could possibly enhance the quality of both statutory and non-statutory information.

The remainder of this chapter is organised as follows. Section 3.2 presents a review of the literature and develops the hypotheses. Research design, including sample construction, descriptive statistics, and correlation analysis, are discussed in Section 3.3. Section 3.4 discusses the results, and Section 3.5 concludes.

3.2 Literature review and hypothesis development

This section starts by reviewing the association between auditor industry specialisation and financial reporting quality. Relevant institutional detail about the role of auditors in monitoring the quality of voluntary disclosure is then considered. Hypotheses about the association between auditor industry specialisation and non-GAAP earnings quality are then illustrated.

3.2.1 Auditor industry specialisation and financial reporting quality

The causes and consequences of auditor industry specialisation have been widely investigated in prior research.[26] This stream of research extends the literature regarding auditor size by investigating whether quality differentiation occurs at the intra-audit firm level. Auditors will choose to specialise if they perceive benefits, such as increased fees or market share from higher quality audits and/or economies of scale. Industry specialists are expected to provide higher audit quality because they have greater knowledge of industry business and accounting practices than non-specialists (Dopuch and Simunic 1982; Craswell et al. 1995). This suggests that auditors with industry specialisation have greater competency in delivering higher quality audit. In addition, industry-specialist auditors have higher reputational capital at stake, providing them with greater incentives to deliver high audit quality (DeFond and Zhang 2014). Furthermore, Burnett et al. (2012) find that firms with specialist auditors are more likely to use real earnings management and less likely to use accrual-based earnings management to meet or beat consensus analysts' forecasts.

The literature on auditor industry specialisation employs several approaches to examine whether an auditor with industry specialisation provides higher quality audits. First, a large number of studies find that national-level specialists are associated with high audit quality proxies such as discretionary accruals (Balsam et al. 2003; Reichelt and Wang 2010), earnings response coefficients (Balsam et al. 2003; Lim and Tan 2008), going-concern opinions (GCs) (Lim and Tan 2008;

[26] For literature reviews of industry specialisation and related audit outcomes including audit quality and audit fees, see Hay et al. (2006), Habib (2011) and Hay (2013).

Reichelt and Wang 2010), benchmark beating (Lim and Tan 2008; Reichelt and Wang 2010), disclosure quality (Dunn and Mayhew 2004), analyst forecast accuracy (Payne 2008), and analyst reliance on accounting information (He et al. 2017). For example, Balsam et al. (2003) compare the unsigned discretionary accruals and earnings response coefficients of firms audited by specialised auditors. They find clients of industry-specialist auditors have lower discretionary accruals and higher earnings response coefficients than clients of non-specialist auditors. Dunn and Mayhew (2004) find that firms audited by auditors with industry specialisation tend to have higher quality for overall disclosure. Further, Lim and Tan (2008) find that the effect of non-audit fees on audit quality is conditional on auditor industry specialisation. Reichelt and Wang (2010) and Payne (2008) show that client-firms of industry-specialist auditors are less likely to meet or beat analysts' earnings forecasts, more likely to be issued a going-concern audit opinion, and have the lowest level of abnormal accruals. He et al. (2017) also find that financial analysts incorporate more common information into their earnings forecasts for firms using industry-specialist auditors.

Another strand of literature focuses on the examination of market reaction to auditor switches and typically finds significantly positive abnormal returns surrounding the dates of switching to auditors with industry specialisation. This is consistent with the notion that investors consider the auditor switch as a positive signal for firm valuation, as auditors with industry specialisation are more likely to provide higher audit quality, thereby reducing the degree of information asymmetry and enhancing firm valuation (Knechel et al. 2007).

The third approach examines audit fee premiums. For instance, Craswell et al. (1995) find that on average, industry-specialist Big 8 auditors earn a 34% premium over non-specialist Big 8 auditors. Their findings suggest that industry expertise is a dimension of the demand for higher quality Big 8 audits. However, after Big8/6 audit firm mergers, Ferguson et al. (2003) find limited support for the ability of the Big 6/5 auditors to obtain fee premiums over non-Big 6/5 for those industries not having specialist auditors. Also, they do not find strong support for the presence of industry-specialist premiums in the post-merger years, but find limited support for the presence of industry leadership premiums.

3.2.2 Institutional details regarding auditors and non-GAAP disclosures

In Australia, an auditor has the responsibility to assure that all statutory and non-statutory information included in an entity's annual report is of sufficient quality. For example, auditing standard ASA 720 requires the auditor to read both financial and non-financial information, and consider whether there is any material inconsistency between the other information and the financial report.[27] "If the auditor identifies that a material inconsistency appears to exist (or becomes aware that the other information appears to be materially misstated), the auditor shall discuss the matter with management" (Para 16, ASA 720). Furthermore, "if the auditor concludes that a material misstatement of the other information exists,

[27] ASA 720 has been in effect since 2006, with an amendment in 2014. Prior to the adoption of International Auditing Standards in 2005, Australian Auditing Standard (AUS) 212 Other Information in Documents Containing Audited Financial Reports has imposed similar requirements since 1995 (Para 11-17, AUS 212). Therefore, auditors' responsibility for statutory and non-statutory information appears to be consistent throughout the sample period (2001–2014).

the auditor shall request management to correct the other information" (Para 17, ASA 720). Since the non-GAAP earnings information is generally disclosed as part of the annual report, auditors have a responsibility to assure the non-GAAP earnings information is of sufficient quality.[28]

In addition, the auditor might also use the non-GAAP earnings figures as the materiality benchmark during the auditing process. When considering what benchmark to be used as a starting point in determining materiality, ASA 320 indicates that financial statement items and their volatility are important considerations (Para A3-A7, ASA320).[29] For example, "when, as a starting point, materiality for the financial report as a whole is determined for a particular entity based on a percentage of profit before tax from continuing operations, circumstances that give rise to an exceptional decrease or increase in such profit may lead the auditor to conclude that materiality for the financial report as a whole is more appropriately determined using a normalised profit before tax from continuing operations figure based on past results" (Para A6, ASA320). In theory, higher quality non-GAAP earnings tend to be less volatile compared with GAAP earnings (Hallman et al. 2017). Thus, if non-GAAP earnings represent a higher

[28] Informal discussions with audit partners from PwC, Ernst and Young, KPMG, and Deloitte confirm that auditors read the non-GAAP earnings information included in annual reports and consider whether there is any material inconsistency between non-GAAP figures and other financial information in the financial reports.

[29] ASA 320 has been in effect since 2006, with amendments in 2009 and 2011 respectively. Prior to the adoption of the International Auditing Standards, the relevant auditing standard is AUS306 Materiality and Audit Adjustments in 2001. AUS 306 states that "the auditor selects benchmark(s) appropriate to the entity's circumstances for a quantitative evaluation of materiality at the financial report level and in relation to individual account balances, classes of transactions and disclosures. For example, an evaluation of materiality based on profit impact may not be appropriate when the entity is a not-for-profit organisation, or when the entity's earnings are volatile."

quality measure of a firm's underlying performance, then it will be used as the benchmark for determining the materiality amount (Hallman et al. 2017). [30]

3.2.3 Hypotheses

Prior literature documents that an industry-specialist auditor possesses greater incentives and competency to provide higher quality audits, consistent with the perspective that industry specialists have greater knowledge of industry business and accounting practices than non-specialists (Dopuch and Simunic 1982; Dunn and Mayhew 2004; DeFond and Zhang 2014). In particular, hiring an industry-specialist auditor can improve both statutory and voluntary disclosure quality (Dunn and Mayhew 2004).

The first hypothesis is built on two rationales. First, non-GAAP disclosures are derived from audited financial reports, though they are beyond the statutory disclosure requirements. Auditors' responsibilities are not just certifying compliance with the accounting standards, but also the assurance of fair presentation (DeFond et al. 2018). As demonstrated by Dunn and Mayhew (2004), an industry-specialist auditor assists clients in enhancing disclosures beyond the

[30] Given that non-GAAP earnings has become a predominant financial metric disclosed by companies and is often touted as a more reliable and less volatile measure of recurring earnings, auditors may choose non-GAAP earnings as the materiality benchmark. Recently, the typical approach to materiality as voluntarily disclosed in some of the 2017 extended audit reports for Australia, or as disclosed in the UK. Using the UK setting, Hallman et al. (2017) reveal that of the 229 companies that report non-GAAP profit-before-tax, auditors of 159 (69%) of these companies rely on non-GAAP profit-before-tax to set the materiality benchmark. Moreover, Eilifsen and Messier Jr (2015) show that seven of the eight largest US public accounting firms use income before taxes or "normalised" earnings as the materiality benchmark. In Australia, the auditing standards do not require disclosure of the materiality threshold. However, in discussions with Big 4 audit partners, they suggest that it is very common to use a non-GAAP measure in determining the materiality benchmark.

minimum requirements of GAAP. Since audited financial reports and voluntary disclosures are complementary mechanisms (Ball et al. 2012), industry-specialist auditors thus can assist clients in enhancing the quality of statutory disclosures and voluntary disclosures such as non-GAAP earnings.

Second, auditors' legal responsibilities regarding statutory and non-statutory information and the use of non-GAAP metrics as the materiality benchmark also suggest possible channels through which auditor industry specialisation could influence the quality of non-GAAP earnings.[31] Since industry-specialist auditors have greater incentives to provide higher quality audit (DeFond and Zhang 2014), industry-specialist auditors will assign more weight to the consistency between statutory and non-statutory earnings. Therefore, industry-specialist auditors are more likely to have concerns in cases where non-GAAP earnings numbers are of low quality, particularly when non-GAAP earnings are used as the materiality benchmark. Accordingly, industry-specialist auditors might raise these concerns and discuss them with managers, the audit committee and the board of directors. Managers, on the other hand, might consider this action as a form of threat (Turley and Zaman 2007)[32] and are therefore less likely to report aggressive non-GAAP earnings numbers in the presence of specialised auditors.

[31] Appendix 3.2 presents anecdotal evidence regarding how auditors use non-GAAP earnings metrics for materiality.

[32] In an interview with a finance director, Turley and Zaman (2007, p.780-781) document that "members of the Audit Committee are assumed to have powers far in excess of that of ordinary mortals ... They are perhaps seen as being very senior people and you wouldn't dream of doing anything other than putting on your best possible presentation for that group of people".

Based on the above discussions, I expect a positive association between auditor industry specialisation and non-GAAP earnings quality. This leads to the following hypothesis:

H1: *Non-GAAP earnings quality is higher for clients of industry-specialist auditors than for clients of non-specialist auditors.*

Given the disclosure of non-GAAP earnings numbers is voluntary and varies substantially across industries and firms, firms from industries where non-GAAP disclosures are prevalent would have more comparable benchmarks of non-GAAP earnings from their industry peers.[33] The availability of comparable benchmarks may limit managers' ability and motivation to report aggressive non-GAAP earnings numbers, since it increases the chance of being identified by market participants (Black et al. 2012; Doyle et al. 2013).[34] On the other hand, firms from industries with a limited number of non-GAAP earnings disclosers would be better able to justify and provide relatively aggressive non-GAAP earnings figures without being detected and criticised by the market. Therefore, I expect that the non-GAAP earnings quality is higher in firms from industries where non-GAAP disclosure is relatively more prevalent. This leads to the following hypothesis:

H2a: *Non-GAAP earnings quality is higher in firms from industries where non-GAAP disclosure is relatively more common.*

[33] Firms in the same industry and fiscal year, and therefore subject to the same general economic shocks, are expected to have a similar accruals and earnings structure (Francis et al. 2014).
[34] Both Black et al. (2012) and Doyle et al. (2013) find that market participants discount positive earnings surprises when accompanied by aggressive non-GAAP earnings, suggesting that the market partially understands the opportunistic nature of the aggressive non-GAAP earnings. It may reduce managers' incentives to report aggressive non-GAAP earnings numbers

Next, this study considers whether the association between industry-specialist auditors and the non-GAAP earnings quality is homogeneous across industries. As discussed in H2a, I expect that the quality of non-GAAP earnings is relatively lower in clients from industries where non-GAAP disclosure is less prevalent. In the absence of comparable benchmarks of non-GAAP earnings from industry peers, auditors with industry specialisation may have an advantage in identifying cases where there is a material inconsistency between non-GAAP and GAAP earnings, thereby enhancing the quality of non-GAAP earnings numbers (Balsam et al. 2003).[35] In contrast, if the quality of non-GAAP is relatively high for firms from industries where non-GAAP disclosure is more prevalent (as predicted in H2a), industry-specialist auditors may have little impact on the quality of non-GAAP earnings reporting (Dunn and Mayhew 2004).[36] Thus, I predict that the auditor's industry experience and expertise would play a more significant role in firms from industries where disclosure of non-GAAP is less prevalent. To compare the relationship between auditor industry specialisation and non-GAAP earnings quality across prevalent and less prevalent industries, the hypothesis is formulated as below:

H2b: *The association between non-GAAP earnings quality and auditor industry specialisation is more pronounced for firms in industries where non-GAAP disclosures are less prevalent.*

---

[35] Balsam et al. (2003) document that the auditor's industry expertise is key factor that restricts the extent to which managers can report aggressive earnings

[36] Dunn and Mayhew (2004) find that the ability of auditor to add value via disclosure quality is limited in firms which have relatively higher earnings quality.

3.3 Research method and sample selection

3.3.1 Variable measurement

Auditor industry specialisation

This study uses four proxies for auditor industry specialisation. The first two proxies are based on the market share of audit fees.[37] As underlined by DeFond et al. (2000), the use of audit fees to measure market share is consistent with the industrial organisation literature in which market share is defined with regard to industrial output. In a recent study, Audousset-Coulier et al. (2016) compare 30 auditor industry specialisation measures and recommend using the audit fees-based measure for auditor industry specialisation.[38] The advantage of using the audit fees-based measure is that it better captures auditor effort because audit fees are a function of the client size, complexity, and riskiness (Audousset-Coulier et al. 2016).

[37] Since auditor industry specialization is unobservable directly, the literature commonly uses the market shares of auditors as the proxy for the industry specialization. However, Minutti - Meza (2013) is critical of the fact that the measure of industry specialization based on market share is not reliable. It is because auditors with large market share are more likely to have larger clients compared with non-specialists. On the other hand, DeFond and Zhang (2014, p.302) argue that "while self-selection is a legitimate concern, it is premature to draw a definite conclusion on this issue and we call for future research to further explore the effect of self-selection in the specialization literature".

[38] Audousset-Coulier et al. (2016, p.158) suggest that "audit fee-based measures should probably be prioritized by researchers and that previous empirical findings based on other measurement variables need to be re-examined".

Similar to Craswell et al. (1995) and Ferguson and Stokes (2002), I measure auditor industry specialisation based on an audit firm's share of total industry audit fees. Auditors are deemed to be an industry-specialist auditor if they attain a 30 per cent or higher market share.[39] In addition, I adopt a more restrictive approach and identify an auditor as a market leader when that auditor has the largest market share, whereby that share is at least ten per cent higher than the second largest market share. A sufficiently larger market share than the second largest industry leader suggests that the industry leader is dominant. The ten percentage point restriction follows prior literature (Balsam et al. 2003; Mayhew and Wilkins 2003; Reichelt and Wang 2010; Audousset-Coulier et al. 2016).

Although Audousset-Coulier et al. (2016) suggest using the audit fee-based measure as a proxy for auditor industry specialisation, the use of one measure for a complex construct potentially leads to a mono-operation bias because it negates the simultaneous and potentially contradictory effect of several aspects of industry specialisation strategies. Therefore, I also measure the industry-specialist auditor and market leader based on the number of clients. Using the number of clients as the base avoids the bias towards large clients introduced by the use of audit fee or sales as the base. Situations, where an auditor has many small clients in an industry and has developed the knowledge base to be a specialist, is more likely to be captured by a measure reflecting the number of clients rather than a fee-based measure (Balsam et al. 2003).

[39] The sample for this study is restricted to non-GAAP disclosers. To mitigate the selection bias, I calibrate the market share of auditors based on the whole population. Accordingly, the 30 per cent market share is for the population. After the consolidation of the Big 6 into Big 4, a Big 4 accounting firm has more than an equal share of an industry if it audits 25 per cent or more of the industry. Therefore, I set the cut-off market share of industry specialisation at 30 per cent to ensure that in every industry the entire Big 4 cannot be classified as specialists.

Non-GAAP earnings and exclusions

Following prior literature (Kolev et al. 2008; Frankel et al. 2011), non-GAAP exclusions (*Exclusions*) are defined as the difference between non-GAAP earnings (*Non_GAAP_Earnings*) and GAAP earnings (*GAAP_Earnings*): *Exclusions* = *Non_GAAP_Earnings*– *GAAP_Earnings*. When non-GAAP earnings are higher than GAAP earnings, *Exclusions* are positive, indicating that the average exclusion is an expense.

Future operating income

The dependent variable is future operating income, defined as earnings per share from operations in t+1. I believe this dependent variable is best suited for examining the research questions because operating income excludes non-recurring special items but includes recurring items that might appear in firms' "other exclusions" from non-GAAP earnings. As such, it best approximates the concept of "permanent earnings". (Kolev et al. 2008; Frankel et al. 2011; Curtis et al. 2014).

Control variables

I include seven control variables in the main regression. Following prior literature (Doyle et al. 2003; Kolev et al. 2008; Frankel et al. 2011; Curtis et al. 2014), I include sales growth (*sg*), firm size (*sizeta*), earnings volatility (*voll12*), leverage (*lev*), an indicator for loss firms (*loss*) and the market-to-book ratio (*mtb*). Prior research demonstrates that each of these variables is correlated with both non-GAAP earnings and future earnings (Doyle et al. 2003; Kolev et al. 2008; Frankel et al. 2011; Curtis et al. 2014). I also include an indicator variable for the use of a Big 4 auditor (*big4*), as I am examining the association between industry-specialist auditors and non-GAAP earnings quality and want to control for the effects of Big 4 auditors on non-GAAP earnings and future operating earnings.

Table 3.1 presents the definitions and measurement of all variables.

Table 3.1 Variable Measurement

Variable	Measurement
Panel A: Earnings variables	
GAAP_Earnings	*GAAP_Earnings* is GAAP earnings per share, calculated as the disclosed GAAP earnings together with non-GAAP earnings collected from a firm's earnings press release divided by the number of total shares outstanding
Non_GAAP_Earnings	*Non_GAAP_Earnings* is non-GAAP earnings per share, calculated as the non-GAAP earnings metric collected from the earnings press release divided by the number of total shares outstanding
Exclusions	Exclusion is the difference between *Non_GAAP_Earnings* and *GAAP_Earnings* (*Exclusion=Non_GAAP_Earnings– GAAP_Earnings*)
Future Operating Income	*Future Operating Income* is earnings per share from operations in t+1
Panel B: Auditor industry specialisation variables	
SP (fees)	An indicator variable for an auditor with industry specialisation equals one if the auditor with industry specialisation, zero otherwise. I define industry specialisation as the audit firm's share of total industry audit fees. Auditors are deemed to be a specialist if they attain a 30 per cent market share of audit fees from this measure.
SP (clients)	An indicator variable for an auditor with industry specialisation equals one if the auditor with industry specialisation, zero otherwise. I define industry specialisation as the audit firm's number of clients. Auditors are deemed to be a specialist if they attain a 30 per cent market share of the number of clients from this measure.
Leader(fees)	An indicator variable for market leader auditor equals one if the auditor is the one with the largest market share of audit fees, where that share also is at least 10 per cent higher than the second largest market share.
Leader(clients)	An indicator variable for market leader auditor equals one if the auditor is the one with the largest market share of the number of clients, where that share also is at least 10 per cent higher than the second largest market share.
Panel C: Firm's characteristics	
lev	Leverage is measured as (Total long-term debt + debt in current liabilities) /Total assets
mtb	*mtb* is the market to book ratio, measured as the market value of equity divided by the book value of equity
sg	Sales growth equals sales in current year t minus sales in year t-1 divided by sales in year t-1
sizeta	Firm size is measured as the natural logarithm of total assets
loss	An indicator variable for loss firms equal one if GAAP earnings in year *t* is less than zero, and zero otherwise
big4	An indicator variable for the use of a Big 4 auditor equals one if the auditor is the Big 4 auditing firms, and zero otherwise
voll12	Earnings volatility is the standard deviation of return on assets (defined as net income divided by total assets) over the past 12 months.

3.3.2 Sample selection

Non-GAAP earnings data for this study is hand-collected from earnings announcements for the Australian Securities Exchange (ASX) 500 firms from 2001 to 2014. Text search technology available from the Securities Industry Research Centre of Asia-Pacific (SIRCA) is used to identify all instances within full-year profit announcements, where a non-GAAP earnings measure was reported by the ASX 500 companies. The non-GAAP earnings data is identified and collected from firms' media release, preliminary financial statements and annual reports using search terms such as "cash earnings", "core earnings", "underlying earnings" and "normalised profit".[40] Non-GAAP earnings are earnings-per-share value reported by managers in their earnings announcement. Consistently, GAAP earnings are defined as earnings per share before extraordinary items and discontinued operations.

The final sample consists of 2237 firm-year observations (non-GAAP disclosers) for the period of 2001–2014. I use the ASPECT Huntleys FinAnalysis financial database to extract accounting information and the SIRCA database to extract auditing information. To mitigate the undue influence of outliers, I winsorise the top and bottom one percentile of key variables used in the regression analysis.[41]

[40] A detailed summary of procedures for identifying and collecting non-GAAP disclosures is conducted by Coulton et al. (2016).
[41] Results remain unchanged when the regressions are run on the unwinsorised data.

3.3.3 Research method

Consistent with Kolev et al. (2008), Frankel et al. (2011) and Curtis et al. (2014), the quality of non-GAAP earnings is tested using the following regression model:

$$Future\ Operating\ Income_{t+1} = \alpha + \beta_1 Non\_GAAP\_Earnings + \beta_2\ Exclusions + \beta_3\ Auditing +$$

$$\beta_4\ Non\_GAAP\_Earnings \times Auditing + \beta_5\ Exclusions \times Auditing + \gamma Controls_i + \varepsilon_i \quad (1)$$

where *Future Operating Income* is earnings per share from operations in t+1; *Non_GAAP_Earnings* is the earnings per share reported by the management for the current period; *Exclusions* is the difference between non-GAAP earnings and GAAP earnings; *Auditing* is a variable representing the variable for specialist auditors (*SP*) or market leaders auditors (*Leader*): *SP* equals one if the auditor has industry specialisation, and zero otherwise; *Leader* equals one if the auditor is the one with the largest market share, and that share is at least 10 per cent higher than the second largest market share; *Controls* are control variables; ε is the error term.

Because all variables, except those indicator variables, are expressed in dollars per share and scaled by total assets per share, the coefficients in Model (1) can be interpreted as the future-dollar implication of a dollar change in the unscaled independent variable. If non-GAAP exclusions are irrelevant and non-recurring, and have no future earnings consequences, then the coefficient on non-GAAP exclusions in Model (1) (i.e., β_2) should be zero. Following prior literature, I expect the coefficient on *Exclusions* to be negative, indicating that a portion of non-GAAP exclusions is recurring expenses (Doyle et al. 2003; Gu and Chen 2004; McVay 2006; Kolev et al. 2008; Frankel et al. 2011).

The estimated coefficient of interest in this regression is β_5. If a non-GAAP discloser audited by an industry-specialist auditor reports higher quality of non-GAAP earnings, I expect β_5 to be positive, countering the expected negative coefficient on *Exclusions*.

To examine whether non-GAAP earnings quality differs in industries with different degrees of non-GAAP disclosure prevalence, I estimate Equation (1) separately for industries classified as having a high propensity to disclose non-GAAP earnings and for all other industries after excluding the variable for specialist auditors and its interaction terms. Accordingly, I test H2a using the following regression model:

$$Future\ Operating\ Income_{t+1} = \alpha + \beta_1 Non\_GAAP\_Earnings + \beta_2\ Exclusions + \gamma Controls_i + \varepsilon_i \quad (2)$$

The estimated coefficient of interest in this regression is β_2. I use a Wald test to compare β_2 estimated from prevalent industries and other industries. If the non-GAAP earnings quality is relatively higher in client-firms from prevalent industries, I expect the magnitude on β_2 to be relatively smaller for client-firms from prevalent industries than that for client-firms from less prevalent industries.

3.4. Results

3.4.1 Descriptive statistics and correlation analysis

Panel A of Table 3.2 provides descriptive statistics on the key variables for the sample of non-GAAP disclosers. The mean dollar value per share of GAAP earnings is \$0.28, while the mean dollar value per share of non-GAAP earnings is \$0.33. Consistently, the median dollar value of non-GAAP earnings is also higher than that for GAAP earnings (\$0.18 vs. \$0.14). Not surprisingly, these patterns reveal that non-GAAP earnings are systematically higher than GAAP earnings. Moreover, 75.1% of non-GAAP disclosers are clients of Big 4 auditors,[42] while 31.5% of non-GAAP disclosers are clients of industry-specialist auditors, and 27.4% of them are audited by market leaders (measured by the market share of audit fees).[43] In contrast, only 5.5% and 21% of non-GAAP disclosers are audited by specialist auditors or market leaders respectively when these variables are measured by the number of clients.

To better understand the audit market structure in Australia, I present a detailed summary of statistics for firm-year non-GAAP disclosers audited by either specialist or market leader auditors across different industries based on two-digit GICS codes. The summary statistics reported in Panel B of Table 3.2 shows that, when specialisation or market leader auditors are measured by the market share of audit fees, 64% of non-GAAP disclosers from the Automobile and

[42] In an international study, Francis et al. (2013) find that in 2335 firm-year observations in Australia between 1997 and 2007, 71% of firms are audited by Big 4 auditors, while the Big 4 audit market Herfindahl index based on is 0.46.
[43] Consistently, Carson et al. (2012) find that 25.6% of firms are audited by market leaders (calculated in terms of audit fee market share) in their Australian sample.

Components industry are audited by specialists, while 50% of non-GAAP disclosers in this industry are audited by market-leader auditors. Similar to Ferguson and Stokes (2002), I also identify a small number of industries with non-Big 4 specialists. Grant Thornton, Lawler Partners, and Horwath are specialists in the industry sections Energy (2012), Health Care Equipment and Services (2012) and No Specified (2003) respectively. In particular, Grant Thornton was also the market leader in the Energy industry in 2012.

Table 3.2 Summary Statistics

The sample contains a maximum 2237 firm-year observations from 2001 to 2014. All variables have been winsorised at percentile bands one and ninety-nine, and are defined in Table 3.1.

Panel A: Summary statistics

Variable	Mean	Std Dev	Q1	Median	Q3	Min	Max
Future Operating Income	0.285	0.538	0.019	0.149	0.377	-0.715	2.249
Non_GAAP_Earnings	0.332	0.478	0.072	0.178	0.393	-0.197	2.777
GAAP_Earnings	0.281	0.584	0.023	0.140	0.355	-1.162	3.084
Exclusions	0.051	0.330	0.000	0.014	0.082	-2.932	3.939
SP(fees)	0.315	0.465	0.000	0.000	1.000	0.000	1.000
Leader (fees)	0.274	0.446	0.000	0.000	1.000	0.000	1.000
SP(clients)	0.055	0.229	0.000	0.000	0.000	0.000	1.000
Leader (clients)	0.210	0.407	0.000	0.000	0.000	0.000	1.000
lev	0.228	0.168	0.096	0.223	0.331	0.000	0.880
mtb	2.389	2.798	0.982	1.609	2.689	0.121	25.170
sg	0.937	8.762	-0.043	0.078	0.281	-0.986	183.089
sizeta	20.188	1.907	18.844	20.325	21.700	13.986	23.153
loss	0.129	0.335	0.000	0.000	0.000	0.000	1.000
big4	0.751	0.432	1.000	1.000	1.000	0.000	1.000
voll12	0.109	0.074	0.062	0.089	0.133	0.021	0.604

Table 3.2 (continued)

Panel B: Audit market structure

Industry Sectors (two-digit SIRCA industry classification codes)	**Non-GAAP disclosers** (firm-year)	**Big 4 Auditors**	**Specialists** (fees)	**Market Leaders** (fees)	**Specialists** (clients)	**Market Leaders** (clients)
Energy	175	78%	28%	25%	0%	27%
Materials (excl Metals and Mining)	149	81%	51%	48%	32%	32%
Metals and Mining	230	74%	27%	24%	0%	20%
Capital Goods	199	79%	49%	45%	0%	37%
Commercial Services and Supplies	181	66%	24%	17%	0%	17%
Transportation	52	79%	37%	25%	2%	0%
Automobile and Components	28	82%	64%	50%	57%	32%
Consumer Durables and Apparel	46	76%	33%	26%	2%	7%
Consumer Services	112	71%	29%	29%	0%	14%
Media	161	84%	36%	36%	4%	38%
Retailing	119	70%	22%	19%	4%	23%
Food and Staples Retailing	37	89%	51%	46%	54%	30%
Food and Drug Retailing	108	85%	34%	19%	0%	26%
Health Care Equipment and Services	106	74%	18%	18%	0%	7%
Pharmaceuticals and Biotechnology	44	68%	41%	41%	34%	34%
Banks	10	100%	60%	40%	60%	50%
Diversified Financials	154	71%	20%	14%	0%	9%
Insurance	8	100%	0%	0%	13%	0%
Real Estate excluding Investment Trusts	18	67%	39%	39%	0%	11%
Real Estate Investment Trusts	1	0%	0%	0%	0%	0%
Software and Services	111	68%	22%	19%	0%	12%
Technology Hardware and Equipment	21	71%	29%	33%	0%	0%
Telecommunication Services	79	82%	33%	30%	0%	16%
Utilities	87	59%	17%	14%	5%	0%
No Specified	1	0%	100%	0%	100%	0%
Total	**2237**	**75%**	**32%**	**27%**	**6%**	**21%**

Table 3.3 reports Pearson and Spearman correlations for the key variables used in the regression analyses. All variables except financial leverage are significantly correlated at 10% level to the dependent variable of the regression analyses, namely *Future Operating Income* in Pearson (Spearman) correlations. As expected, non-GAAP exclusions are negatively associated with *Future Operating Income*. Consistent with the prior literature, it suggests that a portion of non-GAAP exclusions is recurring expenses (Doyle et al. 2003; Gu and Chen 2004; McVay 2006; Kolev et al. 2008; Frankel et al. 2011).

Table 3.3 Correlation Coefficients

Variable	*Future Operating Income*	*Non_GAAP_Earnings*	*GAAP_Earnings*	*Exclusions*	*SP (fees)*	*Leader(fees)*	*SP (clients)*	*Leader(clients)*	*lev*	*mtb*	*sg*	*sizeta*	*loss*	*voll12*	*big4*
Future Operating Income	1.000 .	0.745* 0.00	0.693* 0.00	-0.110* 0.00	0.126* 0.00	0.097* 0.00	0.141* 0.00	0.085* 0.00	0.099* 0.00	0.380* 0.00	0.087* 0.00	0.417* 0.00	-0.405* 0.00	-0.401* 0.00	0.211* 0.00
Non_GAAP_Earnings	0.745* 0.00	1.000* .	0.839* 0.00	-0.020 0.37	0.150* 0.00	0.116* 0.00	0.149* 0.00	0.089* 0.00	0.161* 0.00	0.338* 0.00	0.077* 0.00	0.551* 0.00	-0.471* 0.00	-0.462* 0.00	0.233* 0.00
GAAP_Earnings	0.660* 0.00	0.825* 0.00	1.000 .	-0.409* 0.00	0.120* 0.00	0.091* 0.00	0.125* 0.00	0.095* 0.00	0.070* 0.00	0.373* 0.00	0.145* 0.00	0.415* 0.00	-0.438* 0.00	-0.463* 0.00	0.170* 0.00
Exclusions	-0.092* 0.00	-0.016 0.46	-0.578* 0.00	1.000 .	0.049* 0.02	0.021 0.33	0.033 0.13	0.011 0.63	0.110* 0.00	-0.121* 0.00	-0.136* 0.00	0.065* 0.00	0.090* 0.00	0.122* 0.00	0.067* 0.00
SP (fees)	0.107* 0.00	0.118* 0.00	0.090* 0.00	0.011 0.61	1.000 .	0.288* 0.00	0.896** 0.00	0.448* 0.00	0.095* 0.00	0.016 0.46	-0.100* 0.00	0.215* 0.00	-0.104* 0.00	-0.050* 0.02	0.377* 0.00
Leader(fees)	0.124* 0.00	0.129* 0.00	0.100* 0.00	0.010 0.65	0.896* 0.00	0.294* 0.00	1.000 .	0.473* 0.00	0.087* 0.00	0.022 0.30	-0.074* 0.00	0.205* 0.00	-0.093* 0.00	-0.035 0.11	0.344* 0.00
SP (clients)	0.080* 0.00	0.103* 0.00	0.077* 0.00	0.013 0.53	0.288* 0.00	1.000 .	0.294* 0.00	0.240* 0.00	0.048* 0.03	-0.020 0.35	-0.038* 0.08	0.106* 0.00	-0.041* 0.06	-0.078* 0.00	0.135* 0.00
Leader(clients)	0.078* 0.00	0.069* 0.00	0.074* 0.00	-0.031 0.15	0.448* 0.00	0.240* 0.00	0.473* 0.00	1.000 .	0.054* 0.01	0.010 0.66	-0.036* 0.10	0.144* 0.00	-0.060* 0.01	-0.037* 0.09	0.291* 0.00
lev	-0.007 0.74	-0.003 0.88	-0.041* 0.06	0.068* 0.00	0.075* 0.00	0.036* 0.10	0.065* 0.00	0.033 0.12	1.000 .	-0.009 0.70	-0.022 0.32	0.343* 0.00	-0.193* 0.00	-0.181* 0.00	0.083* 0.00
mtb	0.205* 0.00	0.193* 0.00	0.196* 0.00	-0.069* 0.00	-0.006 0.79	-0.038* 0.08	-0.003 0.91	-0.013 0.54	0.007 0.73	1.000 .	0.199* 0.00	-0.031 0.16	-0.187* 0.00	-0.242* 0.00	0.061* 0.00
sg	-0.055* 0.01	-0.054* 0.01	-0.033 0.13	-0.020 0.35	-0.056* 0.01	-0.016 0.47	-0.049* 0.02	-0.044* 0.04	-0.054* 0.01	-0.005 0.82	1.000 .	-0.070* 0.00	-0.121* 0.00	-0.015 0.50	-0.161* 0.00
sizeta	0.363* 0.00	0.422* 0.00	0.329* 0.00	0.027 0.22	0.223* 0.00	0.105* 0.00	0.211* 0.00	0.150* 0.00	0.337* 0.00	-0.104* 0.00	-0.082* 0.00	1.000 .	-0.315* 0.00	-0.357* 0.00	0.325* 0.00
loss	-0.252* 0.00	-0.249* 0.00	-0.250* 0.00	0.083* 0.00	-0.104* 0.00	-0.041* 0.06	-0.093* 0.00	-0.060* 0.01	-0.169* 0.00	-0.056* 0.01	0.121* 0.00	-0.363* 0.00	1.000 .	0.343* 0.00	-0.175* 0.00
voll12	-0.249* 0.00	-0.256* 0.00	-0.274* 0.00	0.116* 0.00	-0.053* 0.01	-0.067* 0.00	-0.044* 0.04	-0.075* 0.00	-0.150* 0.00	-0.075* 0.00	0.145* 0.00	-0.353* 0.00	0.393* 0.00	1.000 .	-0.147* 0.00
big4	0.159* 0.00	0.166* 0.00	0.118* 0.00	0.031 0.15	0.377* 0.00	0.135* 0.00	0.344* 0.00	0.291* 0.00	0.059* 0.01	0.026 0.23	-0.045* 0.04	0.346* 0.00	-0.175* 0.00	-0.180* 0.00	1.000 .

This table presents the correlation matrix for the selected variables used in the analysis. The sample consists of 2237 firm-year observations between 2001 and 2014. Pearson (Spearman) correlation coefficients are in the lower (upper) triangle.
*significant at the 10% level.

3.4.2 Auditor industry specialisation and non-GAAP earnings quality

For tests of the relationship between auditor industry specialisation and non-GAAP earnings quality, I regress one-year-ahead operating income (*Future Operating Income*) on non-GAAP earnings, non-GAAP exclusions, indicator variables for specialists auditors or market leaders, and their interactions terms. I present the results in Table 3.4. Columns (1) and (2) report results for industry specialist and market leader measured by the market share of audit fees respectively, while Column (3) and (4) report specialist or market leader measured on the number of clients.

The results reported in Table 3.4 Column (1) show that the coefficient on exclusions (β_2) is -0.126 (t =-2.28).[44] As expected, the coefficient on the interaction term between exclusions and auditor industry specialisation (β_5) is positive (β =0.091) and significant (t =2.47), countering the negative coefficient on β_2. These results reveal that one dollar of non-GAAP exclusions is associated with \$0.04 (0.126–0.091) expenses in the future among firms that are audited by auditors with industry specialisation, compared with \$0.13 expenses in the future for firms that are audited by non-specialists. In other words, non-GAAP exclusions reported by firms audited by industry-specialist auditors tend to have less predictability for future operating performance, implying the higher quality of non-GAAP earnings, than firms audited by auditors without industry specialisation. Consistently, results in Column (2) suggest that one dollar of non-GAAP exclusions is associated with \$0.02 (0.133–0.112) expenses in the future

[44] Consistent with prior research, non-GAAP exclusions (β_2) are less persistent than non-GAAP earnings (β_1) (0.126<0.743), but they are not entirely transitory (Doyle et al. 2003; Gu and Chen 2004; Frankel et al. 2011).

among firms that are audited by market leaders, compared with \$0.13 expenses in the future for firms that are audited by non-market leaders. The results in Columns (3) and (4) are consistent with those reported in Columns (1) and (2).

Thus, I find a positive association between auditor industry specialisation and non-GAAP earnings quality across four different measures of industry specialisation, supporting H1. The results demonstrate that non-GAAP exclusions in clients of industry-specialist auditors tend to have less predictive ability in forecasting future performance, indicating that industry-specialist auditors can assist clients to deliver not only higher quality statutory disclosures but also higher quality voluntary disclosures.[45]

Most control variables have significant coefficients and signs consistent with prior research. For example, leverage (*lev*) and the indicator of loss firm (*loss*) are negatively associated with the future operating income (*Future Operating Income*), suggesting firms with higher leverage and loss firms have lower future operating income. On the other hand, the market-to-book ratio (*mtb*) and total assets (*sizeta*) are positively associated with future operating income, indicating firms with higher market-to-book ratio and larger asset size have higher future operating income (Kolev et al. 2008; Curtis et al. 2014).

[45] I have conducted robustness tests for positive non-GAAP exclusions (non-GAAP earnings > GAAP earnings). The results (untabulated) suggest that the positive association between non-GAAP earnings quality and auditor industry specialisation is unchanged among client-firms with positive non-GAAP exclusions. However, there is no significant results for negative exclusions (non-GAAP earnings < GAAP earnings), given there are the relatively smaller amount of observations with negative non-GAAP exclusions (only 533 firm-year observations have negative exclusions).

Table 3.4 Auditor Industry Specialisation and Non-GAAP Earning Quality

This table examines the association between Non-GAAP earnings quality and auditor industry specialisation using Model (1):

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{Exclusions} + \beta_3 \textit{Auditing} + \beta_4 \textit{Non\_GAAP\_Earnings} \times \textit{Auditing} + \beta_5 \textit{Exclusions} \times \textit{Auditing} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Auditing* is a variable representing specialist auditors (*SP*) and market leader auditors (*Leader*), *SP* equals one if the auditor has industry specialisation, and zero otherwise, *Leader* equals one if the auditor is the one with the largest market share, where that share also be at least 10 per cent higher than the second largest market share; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss (*loss*), an indicator for Big 4 auditors and earnings volatility (*voll12*), ε is the error term. Figures in parentheses are *t*-statistics. *** (**, *) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 3.1.

	Specialist (fees)	Market Leader (fees)	Specialist (clients)	Market Leader (clients)
VARIABLES	(1) *Future Operating Income*	(2) *Future Operating Income*	(3) *Future Operating Income*	(4) *Future Operating Income*
Constant	-0.227*	-0.220*	-0.225	-0.238*
	(-1.98)	(-1.97)	(-1.89)	(-2.28)
Non_GAAP_Earnings	0.743***	0.742***	0.769***	0.733***
	(17.74)	(17.11)	(22.20)	(20.48)
Exclusions	**-0.126***	**-0.133****	**-0.116***	**-0.133****
	(-2.28)	**(-2.45)**	**(-2.29)**	**(-2.60)**
SP	-0.010	-	0.019	
	(-0.29)		(0.36)	
Non_GAAP_Earnings×SP	0.042	-	-0.060	
	(0.66)		(-0.57)	
Exclusions×SP	**0.091****	-	**0.345****	
	(2.47)		**(2.56)**	
Leader	-	-0.002		-0.027
		(-0.07)		(-1.26)
Non_GAAP_Earnings× Leader	-	0.045		0.104**
		(0.75)		(3.03)
Exclusions× Leader	-	**0.112****		**0.147****
		(3.25)		**(3.08)**
lev	-0.093**	-0.092*	-0.085**	-0.095*
	(-2.47)	(-2.33)	(-2.39)	(-2.26)
mtb	0.016***	0.016***	0.015***	0.016***
	(10.57)	(10.49)	(9.27)	(12.58)
sg	-0.001	-0.001	-0.001	-0.001
	(-0.81)	(-0.82)	(-0.84)	(-0.91)
sizeta	0.018**	0.018**	0.017**	0.018**
	(2.69)	(2.78)	(2.67)	(3.14)
loss	-0.073*	-0.073*	-0.072*	-0.072*
	(-2.02)	(-2.07)	(-1.99)	(-2.07)
voll12	-0.196	-0.198	-0.179	-0.186
	(-1.08)	(-1.06)	(-1.03)	(-1.04)
big4	0.022	0.020	0.024	0.024
	(0.99)	(0.95)	(1.30)	(1.30)
Industry Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Observations	2,141	2,141	2,141	2,141
Adjusted R-squared	0.576	0.576	0.577	0.578
Wald Test	*Exclusions+Exclusions×SP=0*	*Exclusions+Exclusions ×Leader=0*	*Exclusions+Exclusions×SP=0*	*Exclusions+Exclusions ×Leader=0*
P-value	0.402	0.544	0.127	0.792

3.4.3 Non-GAAP earnings quality: Prevalence of non-GAAP earnings disclosures

Next, I test whether the non-GAAP earnings quality differs in clients from industries with different degrees of non-GAAP disclosure prevalence. In Table 3.5, I divide the sample into two groups, namely industries where non-GAAP disclosures are prevalent and those where they are less prevalent. Based on a detailed survey of Australian non-GAAP disclosures (Coulton et al. 2016), I consider the prevalent industries are those most likely to present non-GAAP information, including Utilities, Consumer Discretionary, Financial and Industrial sectors.[46] Column (1) reports the result for the quality of non-GAAP earnings in clients from prevalent industries, while Column (2) presents the results for clients from less prevalent industries. The results show that non-GAAP exclusions of clients from both prevalent (β_2 = -0.049, t =-2.39) and less prevalent (β_2 =-0.152, t =-2.56) industries are negatively associated with future operating earnings. This is consistent with prior literature, and suggests that a portion of non-GAAP exclusions is recurring expenses (Doyle et al. 2003; Gu and Chen 2004; McVay 2006; Kolev et al. 2008; Frankel et al. 2011).

Importantly, the result from the between equations test for *Exclusions* (β_2) reveals that non-GAAP exclusions of clients from prevalent industries are significantly (p-value =0.086) lower than non-GAAP exclusions of clients from less prevalent industries. Supporting H2a, these results demonstrate that the

[46] Coulton et al. (2016) find that the percentage of non-GAAP disclosers is: Utilities (50%), Consumer Discretionary (39.2%), Financial (41.4%) and Industrial (35.3%) respectively. These sectors are most likely to present non-GAAP information from 2000 to 2014 inclusive, which is primarily aligned with the sample period (2001–2014).

quality of non-GAAP earnings is relatively higher among clients from industries where non-GAAP disclosure is more prevalent.

Table 3.5 Non-GAAP Earnings Quality: Prevalence of Non-GAAP Earnings Disclosures

This table examines whether the non-GAAP earnings quality differs in clients from industries with different degrees of non-GAAP disclosure prevalence using Model (2):

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{ Exclusions} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firm (*loss*), earnings volatility (*voll12*), and an indicator for Big 4 auditors, ε is the error term. Figures in parentheses are *t*-statistics. *** (**,*) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 3.1. *Prevalent industries* are those most likely to present non-GAAP information, including Utilities, Consumer Discretionary, Financial and Industrial Classifications (Coulton et al. 2016).

	Prevalent	**Less prevalent**
VARIABLES	(1) *Future Operating Income*	(2) *Future Operating Income*
Constant	-0.519*	-0.305
	(-2.39)	(-0.76)
Non_GAAP_Earnings	0.738***	0.788***
	(17.66)	(20.19)
Exclusions	**-0.049***	**-0.152***
	(-2.39)	**(-2.56)**
lev	-0.211**	0.024
	(-3.90)	(0.21)
mtb	0.019**	0.016*
	(4.50)	(2.19)
sg	-0.011	-0.000
	(-1.32)	(-0.39)
sizeta	0.032*	0.014
	(2.45)	(0.68)
loss	-0.045*	-0.091
	(-2.50)	(-1.79)
voll12	-0.578**	-0.001
	(-4.10)	(-0.00)
big4	-0.027	0.046
	(-1.11)	(1.15)
Industry Dummy	Yes	Yes
Year Dummy	Yes	Yes
Observations	1,034	905
Adjusted R-squared	0.547	0.605
Between equations test	(1) vs (2)	
$\boldsymbol{\beta_2}$ (P-value)	0.086	

3.4.4 Auditors industry specialisation and non-GAAP earnings quality: Prevalence of non-GAAP earnings disclosures

I next examine whether the prevalence of non-GAAP disclosures is associated with differences in the association between the presence of industry-specialist auditors and the quality of non-GAAP earnings disclosure. In Table 3.6, I also separate the sample into two groups, namely prevalent industries and less prevalent industries. Columns (1) to (4) report the results for specialist/market leader measured by the market share of audit fees, while Columns (5) to (8) report the results for specialist or market-leader measures based on the number of clients. In Columns (1) to (4), the results reveal that non-GAAP exclusions (β_2) have less predictive power for firms from prevalent industries than those in less prevalent industries (0.055<0.169 and 0.068<0.180), confirming the higher quality of non-GAAP earnings for firms from prevalent industries. Importantly, the coefficients of β_5 are found to be close to zero and statistically insignificant for firms from prevalent industries (-0.010 and 0.006 respectively), but the input of industry-specialist auditors (β_5 =0.176, t=2.13) and market leaders (β_5 =0.216, t=2.59) becomes more important in firms from industries where non-GAAP disclosures are less common. Results reported in Columns (5) to (8) display a similar pattern as those in Columns (1) to (4).

Overall, the results in Table 3.6 show that when the sample is divided into prevalent and less prevalent non-GAAP disclosing industries, industry-specialist auditor effects are mostly evident among firms in less prevalent non-GAAP disclosure industries. Consistent with H2b, the results suggest that auditor industry specialisation is significantly related to non-GAAP earning quality in firms from less prevalent industries, indicating that the monitoring role of industry-specialist auditors is more important when non-GAAP disclosures are less common.

Table 3.6 Auditors Industry Specialisation and Non-GAAP Earnings Quality: Non-GAAP Disclosure Prevalence

This table examines the role of non-GAAP disclosure prevalence in the association between Non-GAAP earnings quality and auditors industry specialisation using the following regression model:

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{ Exclusions} + \beta_3 \textit{Auditing} + \beta_4 \textit{ Non\_GAAP\_Earnings} \times \textit{Auditing} + \beta_5 \textit{ Exclusions} \times \textit{Auditing} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Auditing* is a variable representing auditor industry specialisation *(SP)*; and market leader auditors (*Leader*); *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firm (*loss*), earnings volatility (*voll12*) and an indicator for Big 4 auditors, ε is the error term. Figures in parentheses are *t*-statistics. *** (**,*) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 3.1. *Prevalent industries* are those most likely to present non-GAAP information, including Utilities, Consumer Discretionary, Financial and Industrial Classifications (Coulton et al. 2016).

	Specialist (fees)		Market Leader (fees)		Specialist (clients)		Market Leader (clients)	
	Prevalent industries	Less prevalent industries	Prevalent industries	Less prevalent industries	Prevalent industries	Less prevalent industries	Prevalent industries	Less prevalent industries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*Future Operating Income*	*Future Operating Income*	*Future Operating Income*	*Future Operating Income*	*Future Operating Income*	*Future Operating Income*	*Future Operating Income*	*Future Operating Income*
Constant	-0.444***	-0.100	-0.357***	-0.193	-0.336*	-0.134	-0.387***	-0.142
	(-4.22)	(-0.48)	(-3.78)	(-0.82)	(-2.27)	(-0.69)	(-3.71)	(-0.80)
Non_GAAP_Earnings	0.734***	0.767***	0.719***	0.785***	0.792***	0.763***	0.708***	0.760***
	(15.50)	(15.45)	(16.13)	(15.55)	(17.37)	(17.71)	(15.38)	(15.34)
Exclusions (β_2)	**-0.055****	**-0.169****	**-0.068*****	**-0.180****	**-0.061*****	**-0.161****	**-0.075*****	**-0.178*****
	(-3.37)	**(-2.97)**	**(-4.18)**	**(-3.14)**	**(-4.36)**	**(-3.15)**	**(-4.04)**	**(-4.17)**
SP	-0.030	0.013	-	-	0.178*	-0.074	-	-
	(-0.60)	(0.22)			(2.27)	(-0.94)		
Non_GAAP_Earnings×SP	0.059	0.009	-	-	-0.759***	0.073	-	-
	(0.34)	(0.14)			(-8.25)	(0.86)		
Exclusions×SP (β_5)	-0.010	**0.176***	-	-	-0.168	**0.458****	-	-
	(-0.33)	**(2.13)**			(-1.35)	**(2.66)**		
Leader	-	-	-0.041*	0.023	-	-	-0.052**	-0.024
			(-2.13)	(0.46)			(-3.20)	(-0.53)
Non_GAAP_Earnings× Leader	-	-	0.161***	-0.024	-	-	0.278**	0.029
			(6.64)	(-0.34)			(3.04)	(0.46)
Exclusions× Leader (β_5)	-	-	0.006	**0.216****	-	-	0.034	**0.292***
			(0.29)	**(2.59)**			(0.93)	**(1.99)**
lev	-0.201***	0.073	-0.192***	0.081*	-0.167***	0.081	-0.201***	0.092*
	(-4.85)	(1.59)	(-4.78)	(1.91)	(-7.05)	(1.81)	(-4.77)	(1.97)
mtb	0.017***	0.015***	0.017***	0.015***	0.015***	0.015***	0.018***	0.016***
	(5.25)	(4.76)	(4.55)	(5.19)	(8.12)	(5.00)	(5.02)	(6.52)
sg	-0.003	-0.000	-0.003	-0.000	-0.003	-0.000	-0.003	-0.000
	(-0.58)	(-0.59)	(-0.62)	(-0.62)	(-0.61)	(-0.82)	(-0.66)	(-0.98)
sizeta	0.027***	0.009	0.025***	0.009	0.020*	0.011	0.023***	0.011
	(3.92)	(0.91)	(3.67)	(0.88)	(2.26)	(1.15)	(3.55)	(1.25)
loss	-0.053	-0.084	-0.054*	-0.083	-0.063**	-0.080	-0.053*	-0.080
	(-1.87)	(-1.51)	(-2.07)	(-1.51)	(-2.42)	(-1.39)	(-2.02)	(-1.47)

Table 3.6 (continued)

voll12	-0.254	-0.099	-0.238	-0.081	-0.178	-0.096	-0.221	-0.046
	(-1.54)	(-0.34)	(-1.57)	(-0.27)	(-1.69)	(-0.33)	(-1.52)	(-0.18)
big4	0.001	0.050	-0.003	0.050	-0.002	0.059**	-0.003	0.061**
	(0.05)	(1.49)	(-0.08)	(1.74)	(-0.06)	(2.58)	(-0.10)	(2.82)
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,127	1,014	1,127	1,014	1,127	1,014	1,127	1,014
Adjusted R-squared	0.547	0.597	0.549	0.598	0.560	0.600	0.554	0.599
Wald Test	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×Leader*=0	*Exclusions+Exclusions×Leader*=0	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×Leader*=0	*Exclusions+Exclusions×Leader*=0
P-value	0.014	0.956	0.001	0.786	0.111	0.112	0.128	0.553
Between equations test	(1) vs (2)		(3) vs (4)		(5) vs (6)		(7) vs (8)	
β_2 (p-value)	0.045		0.044		0.042		0.119	
β_5 (p-value)	0.014		0.009		0.000		0.008	

3.4.5 Auditor industry specialisation and non-GAAP earnings quality: Big 4 auditors

As per the discussion in Section 3.4.1, I have identified a small number of industries with non-Big 4 specialist auditors. Compared with non-Big 4 auditors, Big 4 auditors are generally found to be more competent and independent, because they invest heavily in auditor training and facilitator programs, and have a broad portfolio of clients (Khurana and Raman 2004). Moreover, Big 4 auditors tend to have relatively high reputation risk (DeAngelo 1981; Skinner and Srinivasan 2012) and litigation risk (Dye 1993; Khurana and Raman 2004). Thus, it is possible that the results documented above merely capture the monitoring role played by Big 4 auditors rather than industry-specialist auditors. To rule out such possibility and control for the effect of brand name, I repeat the test on the restricted sample consisting of firms audited by Big 4 auditors only, so the industry specialisation measures do not reflect a dichotomy between the Big 4 and other accounting firms (Balsam et al. 2003; Dunn and Mayhew 2004). Results in Table 3.7 demonstrate that the positive association between auditor industry specialisation and non-GAAP earnings quality remains unchanged among Big 4 clients across the four measures of industry specialisation.

Table 3.7 Auditor Industry Specialisation and Non-GAAP Earnings Quality: Big 4 Subsample

This table examines the association between Non-GAAP earnings quality and auditor industry specialisation in Big 4 subsample using the following regression model:

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{Exclusions} + \beta_3 \textit{Auditing} + \beta_4 \textit{Non\_GAAP\_Earnings} \times \textit{Auditing} + \beta_5 \textit{Exclusions} \times \textit{Auditing} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Auditing* is a variable representing specialist auditors (*SP*) and market leader auditors (*Leader*), *SP* equals one if the auditor has industry specialisation, and zero otherwise, *Leader* equals one if the auditor is the one with the largest market share, where that share also be at least 10 per cent higher than the second largest market share; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator of loss (*loss*) and earnings volatility (*voll12*), *ε* is the error term. Figures in parentheses are *t*-statistics. *** (**, *) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 3.1.

	Specialist (fees)	Market Leader (fees)	Specialist (clients)	Market Leader (clients)
VARIABLES	(1) *Future Operating Income*	(2) *Future Operating Income*	(3) *Future Operating Income*	(4) *Future Operating Income*
Constant	-0.163	-0.161	-0.163	-0.183
	(-0.83)	(-0.78)	(-0.78)	(-0.91)
Non_GAAP_Earnings	0.804***	0.801***	0.812***	0.780***
	(40.72)	(28.49)	(28.84)	(26.97)
Exclusions	**-0.091****	**-0.100****	**-0.088****	**-0.101****
	(-2.52)	**(-3.07)**	**(-2.88)**	**(-3.13)**
SP	0.017	-	0.015	-
	(0.52)		(0.27)	
Non_GAAP_Earnings×SP	-0.020	-	-0.112	-
	(-0.37)		(-1.07)	
Exclusions×SP	**0.057***	-	**0.300****	-
	(1.80)		**(2.56)**	
Leader	-	0.023	-	-0.009
		(0.80)		(-0.42)
Non_GAAP_Earnings× Leader	-	-0.015	-	0.050
		(-0.30)		(1.50)
Exclusions× Leader	-	**0.080*****	-	**0.112***
		(4.63)		**(2.14)**
lev	-0.094	-0.095	-0.086	-0.099
	(-1.55)	(-1.50)	(-1.50)	(-1.48)
mtb	0.015***	0.015***	0.014***	0.016***
	(4.80)	(4.80)	(4.05)	(5.31)
sg	-0.001	-0.001	-0.001	-0.001
	(-0.61)	(-0.62)	(-0.67)	(-0.69)
sizeta	0.015	0.015	0.014	0.016
	(1.82)	(1.70)	(1.67)	(1.87)
loss	-0.092**	-0.092**	-0.091**	-0.091**
	(-3.37)	(-3.37)	(-3.41)	(-3.44)
voll12	-0.213	-0.216	-0.180	-0.189
	(-0.99)	(-0.97)	(-0.91)	(-0.89)
Industry Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Observations	1,635	1,635	1,635	1,635
Adjusted R-squared	0.603	0.604	0.606	0.604
Wald Test	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×Leader*=0	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×Leader*=0
P-value	0.402	0.570	0.111	0.824

3.4.6 Endogenous selection of an industry-specialist auditor

I endeavour to address endogeneity concerns arising from the selection bias of an industry-specialist auditor in several ways. First, I use a two-stage Heckman (1979) procedure, where the first stage regression models the selection of an auditor with industry specialisation and the second stage includes the inverse Mills ratio (*IMR*) as an additional variable in the regression. Following Lennox et al. (2012) and He et al. (2017), the first stage regression models the selection of an auditor with industry specialisation or a market leader as a function of firm size (*sizeta*), property plant and equipment as a percentage of total assets (*ppeat*), the sum of receivables and inventory as a percentage of total assets (*rectinvtat*), leverage (*lev*), an indicator of reporting a loss (*loss*), return on assets (*roa*), liquidity (total current assets scaled by total current liabilities, *curratio*), the issuance of debt during the reporting period (*hasdebt*), and the change of audit firm (*Audit Firm Change*). *Audit Firm Change* is included in the first stage models, but excluded from the second stage models, since it does not be associated with future operating incomes.

The results are reported in Table 3.8. Panel A of Table 3.8 reports results for the first stage of the Heckman selection model on four different measures of auditor industry specialisation. Columns (1) and (2) report results for the auditor industry specialisation measure based on market share of audit fees, while Columns (3) and (4) report results for the measure based on the number of clients. The results show that *Audit Firm Change* is negatively associated with proxies for auditor industry specialisation, except for specialisation measured by the number of clients. However, the result shows that *curratio* is positively associated with

SP(clients). These results demonstrate that exogenous independent variables from the first stage choice model that can be validly excluded from the set of independent variables in the second stage regression (Lennox et al. 2012).

Panel B shows the results for the second stage of the Heckman selection model. Columns (1) and (2) report results for the auditor industry specialisation measure based on market share of audit fees, while Columns (3) and (4) report results for the measure based on the number of clients. In Columns (1) and (2), when the estimated *IMR* is included as an additional regressor, the coefficient on *IMR* is positive and significant (β =0.412, t =2.09 and β =0.665, t =2.78 respectively). Importantly, the coefficients on *Exclusions*×*SP* (β_5 =0.076, t =2.09) and *Exclusions*×*Leader* (β_5 =0.095, t =2.93) continue to be positive and significant, as opposed to the negative coefficients on *Exclusions*[47]. The results are consistent with those reported in Table 3.4.

[47] Similar results are found in Columns (3) and (4).

Table 3.8 Endogenous Selection of an Industry-Specialist Auditor: Heckman Selection Model

This table examines the determinants of selecting an industry-specialist auditor and subsequently the estimation of auditor specialisation effects on non-GAAP earnings quality, using the following regression models:

Stage 1: *Probit (Auditing)* $= \beta_1 lev + \beta_2 sizeta + \beta_3 loss + \beta_4\, ppeat + \beta_5\, rectinvtat + \beta_6 hasdebt + \beta_7\, curratio + \beta_8 roa + \beta_9 Audit\ Firm\ Change$

Stage 2: *Future Operating Income*$_{t+1} = \alpha + \beta_1 Non\_GAAP\_Earnings + \beta_2\, Exclusions + \beta_3\, Auditing + \beta_4\, Non\_GAAP\_Earnings \times Auditing + \beta_5\, Exclusions \times Auditing + \gamma Controls_i + \gamma_2\ IMR\ \varepsilon_i$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Auditing* is a variable representing auditor industry specialisation *(SP)*; and market leader auditors (*Leader*); *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firm (*loss*), earnings volatility (*voll12*), an indicator for Big 4 auditors, PPE scale by total assets (*ppeat*), the sum receivable and inventory scale by total assets (*rectinvtat*), indicator variable of issue of debt (*hasdebt*), the current ratio (*curratio*) and the return on assets (*roa*); *IMR* is the inverse Mills' ratio; ε is the error term. Figures in parentheses are *t*-statistics. *** (**,*) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 3.1.

Panel A: First Stage	**Specialist (fees)**	**Market Leader (fees)**	**Specialist (clients)**	**Market Leader (clients)**
	(1)	(2)	(3)	(4)
VARIABLES	*SP*	*Leader*	*SP*	*Leader*
Constant	-4.687***	-4.891***	-1.957***	-3.206***
	(-20.71)	(-20.84)	(-3.26)	(-13.14)
lev	-0.168	-0.154	0.233	0.211*
	(-1.46)	(-1.29)	(0.88)	(1.68)
sizeta	0.212***	0.209***	0.116***	0.126***
	(19.51)	(18.64)	(4.63)	(10.76)
loss	0.092*	0.090*	0.293**	0.014
	(1.96)	(1.84)	(2.46)	(0.27)
ppeat	-0.095	-0.032	-0.073	-0.199**
	(-1.20)	(-0.40)	(-0.34)	(-2.27)
rectinvtat	0.384***	0.280**	0.336	0.263**
	(3.56)	(2.50)	(1.39)	(2.24)
hasdebt	0.025	0.053	-0.029	-0.022
	(0.52)	(1.06)	(-0.24)	(-0.43)
curratio	-0.001	-0.001	0.021***	-0.001
	(-0.28)	(-0.30)	(3.72)	(-0.31)
roa	-0.015	0.028	0.303	0.003
	(-0.21)	(0.38)	(1.61)	(0.04)
Audit Firm Change	-0.219***	-0.254***	-0.011	-0.259***
	(-3.76)	(-4.11)	(-0.08)	(-4.02)
Industry Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Observations	9,035	9,035	2,385	9,024
Pseudo R-squared	0.096	0.094	0.179	0.085

Table 3.8 (continued)

Panel B: Second Stage	Specialist (fees)	Market Leader (fees)	Specialist (clients)	Market Leader (clients)
VARIABLES	(1) *Future Operating Income*	(2) *Future Operating Income*	(3) *Future Operating Income*	(4) *Future Operating Income*
Constant	0.131	0.362	-0.374*	-0.222
	(0.60)	(1.30)	(-2.15)	(-1.63)
Non_GAAP_Earnings	0.758***	0.753***	0.901***	0.743***
	(17.43)	(18.10)	(17.11)	(20.66)
Exclusions	**-0.118***	**-0.123***	**-0.047****	**-0.124****
	(-2.08)	**(-2.28)**	**(-2.85)**	**(-2.46)**
SP	-0.008	-	0.033	-
	(-0.24)		(0.69)	
Non_GAAP_Earnings ×SP	0.017	-	-0.187	-
	(0.26)		(-1.65)	
Exclusions×SP	**0.076***	-	**0.259****	-
	(2.09)		**(2.39)**	
Leader	-	0.003		-0.021
		(0.11)		(-0.96)
Non_GAAP_Earnings × Leader	-	0.018		0.083*
		(0.32)		(2.03)
Exclusions× Leader	-	**0.095****		**0.142****
		(2.93)		**(2.94)**
lev	-0.093	-0.086	-0.116	-0.131**
	(-1.83)	(-1.68)	(-1.67)	(-3.13)
mtb	0.017***	0.017***	0.011**	0.017***
	(6.72)	(6.76)	(2.59)	(8.29)
sg	-0.001	-0.001	0.009***	-0.001
	(-0.78)	(-0.74)	(3.79)	(-0.84)
sizeta	-0.006	-0.020	0.017*	0.017
	(-0.35)	(-1.04)	(2.07)	(1.62)
loss	-0.092*	-0.100**	-0.035	-0.081*
	(-2.29)	(-2.47)	(-0.64)	(-2.19)
voll12	-0.178	-0.171	-0.418	-0.178
	(-0.76)	(-0.75)	(-1.38)	(-0.72)
big4	0.002	-0.002	-0.025	0.006
	(0.10)	(-0.13)	(-1.04)	(0.29)
IMR	0.412*	0.665**	0.482*	0.141
	(2.09)	(2.78)	(1.81)	(0.67)
Industry Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Observations	1,931	1,931	685	1,931
Adjusted R-squared	0.586	0.587	0.525	0.586
Wald Test	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×Leader*=0	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×Leader*=0
P-value	0.360	0.447	0.098	0.718

Although the Heckman selection model is a popular treatment for the endogeneity issue, Lennox et al. (2012) argue that conclusions about the existence and direction of selection bias (and therefore, the extent to which results are robust to such biases) are entirely dependent on the choice of exclusion restrictions. One possible alternative is the use of propensity scores to create a "matched" sample, in the manner suggested by Lawrence et al. (2011), Minutti-Meza (2013) and He et al. (2017). Propensity score matching (PSM) assumes selection occurs only on the variables used to identify the matched sample, and is premised on the assumption that an appropriate comparison is between (in this case) firms using an auditor identified as higher quality and those which, in some respects "should" make such a choice but do not.

I follow Minutti-Meza (2013) and He et al. (2017) and choose a set of characteristics for matching, including firm size (*sizeta*), property, plant and equipment (*ppeat*), the sum of receivables and inventories (*rectinvtat*), leverage (*lev*), a loss dummy (*loss*), liquidity (*curratio*), return on assets (*roa*) and a dummy variable capturing debt issuance (*hasdebt*), as well as year and industry fixed effects. For PSM, I first estimate a probit model of auditor choice using firm characteristics, and then obtain the propensity score which is basically the estimated probability of hiring an industry-specialist or market leader auditor. Following Lawrence et al. (2011), I then match, without replacement, a non-specialist client with a specialist or market-leader client that has the closest predicted value within a maximum distance of 3 per cent. I report results for the PSM matching approach in Table 3.9.

Panel A Table 3.9 presents means of the treatment and control groups along with the *t*-stat for *t*-test. Results reported in Panel A show that there is no significant difference between treatment and control groups for most of the dependent and independent variables, except for *big4*. These results suggest that the covariates are generally balanced across the treatment and control samples, and that differences in these observed variables across the treatment and control groups are not likely to confound our estimates of the average treatment effect (Armstrong et al. 2010).

Panel B Table 3.9 reports the results for the multivariate analysis using the PSM approach.[48] The results of Columns (1) and (2) suggest that both coefficients on *Exclusions×SP* (β_5 =0.132, t =3.52) and *Exclusions×Leader* (β_5 =0.106, t =2.47) are positive and significant, countering the negative coefficients on *Exclusions*.[49] These results are again consistent with the main results reported previously.

[48] Columns (1) and (2) report results for the measure of auditor industry specialisation based on the market share of audit fees, while Columns (3) and (4) report results for the measure of auditor industry specialisation based on the number of clients.
[49] Similar results are found in Columns (3) and (4).

Table 3.9 Endogenous Selection of an Industry-Specialist Auditor: Propensity Score Matching

This table examines the association between Non-GAAP earnings quality and auditor industry specialisation using the following regression models:

$$Future\ Operating\ Income_{t+1} = \alpha + \beta_1 Non\_GAAP\_Earnings + \beta_2\ Exclusions + \beta_3\ Auditing + \beta_4\ Non\_GAAP\_Earnings \times Auditing + \beta_5\ Exclusions \times Auditing + \gamma Controls_i + \gamma_2\ IMR\ \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is the earnings numbers reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Auditing* is a variable representing the auditor's industry specialisation *(SP)*; and market leader auditors (*Leader*); *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firm (*loss*), earnings volatility (*voll12*), an indicator for Big 4 auditors; ε is the error term. Figures in parentheses are *t*-statistics. *** (**,*) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 3.1.

Panel A	**Treated**	**Controls**		**Treated**	**Controls**		**Treated**	**Controls**		**Treated**	**Controls**	
	***SP(fees)*=1**	***SP(fees)*=0**		***Leader (fees)*=1**	***Leader (fees)*=0**		***SP (clients)*=1**	***SP (clients)*=0**		***Leader (clients)*=1**	***Leader (clients)*=0**	
Variable	Mean	Mean	*t*-stat	Mean	Mean	*t*-stat	Mean	Mean	*t*-stat	Mean	Mean	*t*-stat
Future Operating Income	0.380	0.335	1.42	0.404	0.327	2.26	0.474	0.369	1.37	0.376	0.303	1.88
Non_GAAP_Earnings	0.425	0.386	1.39	0.443	0.376	2.27	0.549	0.454	1.28	0.406	0.393	0.39
Exclusions	0.058	0.053	0.27	0.058	0.046	0.59	0.071	0.020	1.21	0.033	0.065	-1.34
lev	0.248	0.241	0.82	0.247	0.250	-0.39	0.254	0.253	0.05	0.240	0.241	-0.09
mtb	2.277	2.149	1.01	2.288	2.201	0.62	1.901	2.448	-2.09	2.233	2.138	0.62
sg	0.230	0.598	-1.26	0.255	0.383	-0.84	0.374	0.160	0.85	0.208	0.305	-0.99
sizeta	20.873	20.839	0.39	20.900	20.854	0.50	21.071	21.133	-0.31	20.803	20.750	0.50
loss	0.073	0.085	-0.80	0.074	0.075	-0.11	0.067	0.059	0.27	0.085	0.070	0.86
voll12	0.103	0.099	1.00	0.103	0.096	1.93	0.088	0.081	0.91	0.098	0.102	-0.94
big4	0.997	0.719	16.09	0.998	0.742	14.23	1.000	0.790	5.60	1.000	0.752	12.30

Table 3.9 (Continued)

Panel B	Specialist (fees)	Market Leader (fees)	Specialist (clients)	Market Leader (clients)
VARIABLES	(1) *Future Operating Income*	(2) *Future Operating Income*	(3) *Future Operating Income*	(4) *Future Operating Income*
Constant	-0.365**	-0.386*	-0.820	-0.170
	(-2.81)	(-1.91)	(-1.26)	(-0.72)
Non_GAAP_Earnings	0.791***	0.782***	0.579**	0.777***
	(19.17)	(12.28)	(2.80)	(11.69)
Exclusions	**-0.165****	**-0.126***	**-0.071**	**-0.162****
	(-2.62)	**(-1.88)**	**(-0.64)**	**(-2.54)**
SP	0.012	-	-0.035	-
	(0.44)		(-0.31)	
Non_GAAP_Earnings×SP	-0.024	-	0.087	-
	(-0.51)		(0.46)	
Exclusions×SP	**0.132*****	-	**0.330***	-
	(3.52)		**(2.21)**	
Leader	-	-0.009	-	-0.025
		(-0.18)		(-1.72)
Non_GAAP_Earnings× Leader	-	-0.006	-	0.094*
		(-0.09)		(2.31)
Exclusions× Leader	-	**0.106****	-	**0.157*****
		(2.47)		**(4.05)**
lev	-0.106	-0.125**	-0.191*	-0.098
	(-1.78)	(-3.20)	(-2.08)	(-1.34)
mtb	0.022***	0.022***	0.020*	0.010**
	(6.26)	(3.55)	(1.98)	(2.68)
sg	0.000	0.000	-0.002	0.001
	(1.07)	(0.38)	(-0.37)	(1.22)
sizeta	0.020**	0.017	0.046	0.010
	(2.91)	(1.75)	(1.43)	(0.87)
loss	-0.111*	-0.153***	-0.042	-0.087**
	(-2.16)	(-4.26)	(-0.77)	(-2.58)
voll12	-0.285	-0.096	-1.801*	-0.237
	(-1.19)	(-0.54)	(-1.98)	(-0.86)
big4	0.027	0.103*	0.129	0.036
	(0.74)	(2.27)	(1.13)	(1.84)
Industry Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Observations	1,418	1,210	237	887
Adjusted R-squared	0.574	0.599	0.610	0.568
Wald Test	*Exclusions+Exclusions×SP=0*	*Exclusions+Exclusions×Leader=0*	*Exclusions+Exclusions×SP=0*	*Exclusions+Exclusions×Leader=0*
P-value	0.619	0.575	0.016	0.938

3.4.7 Auditor industry specialisation and non-GAAP earnings quality: Around the IFRS adoption

Finally, I examine whether the positive association between auditor industry specialisation and the quality of non-GAAP earnings varies around the mandatory adoption of IFRS in 2005. Li and Yang (2016) document an increase in the frequency of management earnings forecasts following the mandatory IFRS adoption and suggest that IFRS adoption alters firms' disclosure incentives in response to increased capital market demand. I consider the mandatory adoption of IFRS in Australia as an exogenous shock to accounting disclosure practice and examine the role of auditors in monitoring the quality of non-GAAP earnings around the IFRS adoption. The results for the adoption of IFRS are presented in Table 3.10. Comparing the periods before (2001–2004) and after (2006–2014) the adoption of IFRS,[50] the results in Table 3.10 indicate that a positive association between non-GAAP earnings quality and industry-specialist auditors (β_5 =0.042, t=0.45 vs. β_5 =0.117, t=1.80) or market leaders auditors (β_5 =0.111, t=1.37 vs. β_5 =0.116, t=1.99) is stronger in the post-IFRS period, compared with the pre-IFRS era. These results support the expectation that industry-specialist auditors have a more significant impact on the quality of non-GAAP earnings in the post-IFRS adoption era, when firms' disclosure incentives changed and the principle-based accounting standards are implemented.

[50] I do not include 2005 to avoid the transition effect arising from the adoption of IFRS.

Table 3.10 Auditor Industry Specialisation and Non-GAAP Earning Quality: Around IFRS Adoption

This table examines the association between Non-GAAP earnings quality and auditor industry specialisation using the following regression model:

$$Future\ Operating\ Income_{t+1} = \alpha + \beta_1 Non\_GAAP\_Earnings + \beta_2\ Exclusions + \beta_3 Auditing + \beta_4\ Non\_GAAP\_Earnings \times Auditing + \beta_5\ Exclusions \times Auditing + \gamma Controls_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Auditing* is a variable representing the auditor's industry specialisation *(SP)*; and market leader auditors (*Leader*); *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firm (*loss*), earnings volatility (*voll12*) and an indicator for Big 4 auditors (*big4*), ε is the error term. Figures in parentheses are *t*-statistics. *** (**,*) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 3.1.

	Before (2001-2004)	After (2006-2014)	Before (2001-2004)	After (2006-2014)
VARIABLES	(1) *Future Operating Income*	(2) *Future Operating Income*	(3) *Future Operating Income*	(4) *Future Operating Income*
Constant	-0.577**	-0.370	-0.596**	-0.372
	(-2.82)	(-1.74)	(-2.85)	(-1.71)
Non_GAAP_Earnings	0.568***	0.777***	0.601***	0.759***
	(6.26)	(33.70)	(5.69)	(23.48)
Exclusions (β_2)	**-0.125****	**-0.163****	**-0.155****	**-0.159****
	(-2.64)	**(-2.74)**	**(-2.75)**	**(-2.86)**
SP	-0.076	-0.012	-	-
	(-1.71)	(-0.48)		
Non_GAAP_Earnings×SP	0.423**	-0.031	-	-
	(3.21)	(-0.50)		
Exclusions×SP (β_5)	0.042	**0.117***	-	-
	(0.45)	**(1.80)**		
Leader	-	-	-0.050	-0.003
			(-1.09)	(-0.13)
Non_GAAP_Earnings× Leader	-	-	0.333	0.007
			(1.89)	(0.13)
Exclusions× Leader (β_5)	-	-	0.111	**0.116***
			(1.37)	**(1.99)**
lev	-0.119	-0.130**	-0.122	-0.140**
	(-1.57)	(-3.29)	(-1.54)	(-3.35)
mtb	0.009**	0.021***	0.010**	0.021***
	(3.00)	(4.66)	(3.34)	(4.52)
sg	-0.001**	-0.001	-0.001**	-0.001
	(-3.13)	(-0.37)	(-2.80)	(-0.36)
sizeta	0.033**	0.020	0.033**	0.020
	(2.90)	(1.72)	(2.91)	(1.72)
loss	-0.048	-0.093	-0.042	-0.093*
	(-1.34)	(-1.87)	(-1.14)	(-1.93)
voll12	0.073	-0.126	0.073	-0.137
	(0.71)	(-0.49)	(0.71)	(-0.53)
big4	0.058	-0.020	0.063	-0.027
	(1.38)	(-0.47)	(1.64)	(-0.60)
Industry Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Observations	730	1,281	730	1,281
Adjusted R-squared	0.526	0.588	0.517	0.587
Wald Test	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×SP*=0	*Exclusions+Exclusions×Leader*=0	*Exclusions+Exclusions×Leader*=0
	0.507	0.094	0.731	0.074
Between equations test	(1) vs (2)		(3) vs (4)	
β_2 (χ^2)	0.544		0.934	
β_5 (χ^2)	0.594		0.966	

3.5 Conclusion

Non-GAAP earnings disclosures are increasingly more prevalent. Although non-GAAP earnings disclosure is beyond the statutory disclosure requirements and considered as a form of voluntary disclosures, the disclosure of non-GAAP earnings numbers is derived directly from statutory earnings numbers. More importantly, the auditing standards require auditors to consider whether there is any significant difference between the statutory earnings and non-statutory earnings included in annual reports, and auditors may use non-GAAP earnings as the materiality benchmark during the auditing process.

In this study, I examine whether the reporting quality of non-GAAP earnings is associated with an important auditor attribute, namely auditor industry specialisation. Using a sample of ASX 500 firms with the hand-collected non-GAAP earnings data over 2001–2014, I find evidence that clients of industry-specialist auditors tend to disclose higher quality of non-GAAP earnings, compared with those hiring non-specialist auditors. Further, the results suggest that non-GAAP earnings quality are relatively higher in clients from industries where non-GAAP disclosure is prevalent. Importantly, I also find that the effect of industry-specialist auditors on the quality of non-GAAP earnings is relatively more significant in firms from industries where non-GAAP disclosures are less common, or in the post-IFRS adoption period. Although the endogenous choice of auditor is handled by use of the Heckman procedure, and the propensity score matching approach, it is not possible to entirely eliminate the possible explanation of endogeneity between identification of the specialist and the attributes of clients. Therefore, the results must be interpreted with respect to this residual limitation.

Overall, these results support the view that industry-specialist auditors assist clients to improve not only statutory disclosure quality but also voluntary disclosure quality. Collectively, this study provides a better understanding for auditors, regulators, and investors of how auditors could have an impact on the quality of voluntarily disclosed non-GAAP earnings in practice.

Chapter Four: Audit Partner Change and Non-GAAP Earnings Quality

4.1. Introduction

This study aims to examine whether the change of audit partners [51] influences the quality of voluntary disclosure. [52] More specifically, this study examines the association between audit partner change and the quality of alternative and unaudited performance measures voluntarily disclosed by management (i.e., non-GAAP earnings). Non-GAAP earnings figures are typically derived from GAAP earnings by excluding certain items argued to be one-off, non-operating or non-cash (or any combination of these). Since non-GAAP earnings numbers do not comply with accounting standards, managers have substantial discretion over their measurement and reporting.

The rapid growth in the reporting of non-GAAP earnings metrics[53] raises considerable concerns regarding the quality of alternative financial performance metric,[54] because the disclosed non-GAAP earnings are found to be systematically

[51] Following prior studies (Liu and Simunic 2005; Knechel et al. 2015), the terms "auditor" and "audit partner" are used interchangeably in this study.
[52] The purpose of this study is to provide first evidence for the association between audit partner change and non-GAAP earnings quality. Thus, this study focuses on "partner change" effects on the quality of non-GAAP earnings, and does not attempt to separately to identify likely instances of partner rotation as distinct from other reasons for partners no longer continuing (e.g., retirement). It also does not attempt to distinguish between mandatory and voluntary partner changes.
[53] For example, Entwistle et al. (2005) show that 77% of the S&P 500 US firms reported non-GAAP earnings figures in 2001, while Bhattacharya et al. (2004) show that from 1998 to 2000 there was a very substantial increase in such non-GAAP disclosures. Similarly, Zhang and Zheng (2011) find the frequency of non-GAAP reporting increased significantly over the period 1998–2001.
[54] For example, Hans Hoogervorst, the chair of the International Accounting Standards Board (IASB), stated in a speech at the 2016 Annual Conference of the European Accounting Association (EAA) that: "more than 88% of the S&P 500 currently disclose non-GAAP metrics in their earnings release. Of those releases, 82% show increased net income and are clearly designed to present results in a more favourable light. One study showed that the popular metric 'core earnings' was on average 30% higher than GAAP earnings. While these are numbers for the US

higher than the corresponding GAAP earnings, which may substantially mislead capital market participants. This view is supported by prior evidence that managers appear to use non-GAAP earnings measures to meet earnings benchmarks (Bhattacharya et al. 2004; Heflin and Hsu 2008; Black and Christensen 2009).[55] As such, regulators have questioned whether auditors should play a more significant role in verifying or even attesting to non-GAAP calculations (Black and Christensen 2018).

Although non-GAAP earnings numbers disclosed in annual reports are not strictly subject to audit, auditors are legally responsible for the quality of both statutory and non-statutory information (other than the financial report and the auditor's report thereon) included in an entity's annual report.[56] Auditors' responsibilities are firmly rooted in authoritative auditing standards, accounting standards and regulations, which require not just certifying compliance with accounting standards, but also the assurance of fair presentation, and hence compels auditors to consider the economic substance of management's disclosure (DeFond et al. 2018). As required by auditing standards, auditors need to identify any material inconsistency between GAAP and non-GAAP earnings figures based on their acquired knowledge and the context of the audit evidence obtained during the audit. In addition, auditors often use the disclosed non-GAAP earnings

---

market, securities regulators in the world of IFRS Standards are also concerned that non-GAAP numbers are getting increasingly detached from reality (Hoogervorst 2016)."

[55] Bhattacharya et al. (2004) document that the average GAAP EPS is a net loss of 14.7 cents per share (1998–2000), while the corresponding non-GAAP average for the same set of observations is a net income of 8.5 cents per share. Heflin and Hsu (2008) also document a modest decline in the propensity of non-GAAP earnings to meet or beat analysts' forecasts. Black and Christensen (2009) document that managers frequently exclude items that are not "one-off" in nature, since three of the most frequently-used exclusions are recurring items, namely research and development expenses, depreciation and amortisation, and share-based compensation.

[56] See Section 4.2.2 for more details. The relevant auditing standard in Australia is Auditing Standard ASA 720: The Auditor's Responsibilities Relating to Other Information.

numbers as the materiality benchmark (PricewaterhouseCoopers 2011; Eilifsen and Messier Jr 2015; Hallman et al. 2017).[57] Given the importance of non-GAAP metrics in the auditing process, examination of the relationship between auditor attributes and the quality of non-GAAP earnings disclosures is warranted.

Audit partner change is now required in many jurisdictions as a means of enhancing audit independence (Firth et al. 2012). Supporters of audit partner change argue that "long auditor tenure can lead to overfamiliarity with client management and reluctance to resist pressure from the client regarding accounting policy choices" (Stewart et al. 2016, p.181). Audit partner change has also been viewed as a less-costly alternative to audit firm change (Hamilton et al. 2005) by potentially achieving the similar objective of encouraging a fresh approach to the audit. Both regulators and professional bodies believe that greater audit independence should lead to improved audit quality and hence improved financial reporting quality (Fargher et al. 2008; Manry et al. 2008).

Empirical research on the effect of audit partner change is limited due to lack of data, as few jurisdictions require the disclosure of audit partners' names in audit reports. This line of research thus far has documented conflicting evidence on the association between audit partner change and the quality of GAAP earnings. On the one hand, audit partner change is expected to enhance the independence of auditors and bring "fresh eyes" to the accounting choices and disclosure policies of

[57] The relevant Australian auditing standard is ASA 320 Materiality in Planning and Performing an Audit.

clients ("the fresh eyes hypothesis").[58] Consistent with this notion, prior literature documents that a change of audit partner brings better audit quality as reflected in less abnormal (total or working capital) accruals, higher propensity to issue a going-concern audit opinion for financially distressed companies, and less likelihood of meeting or beating earnings benchmarks (Hamilton et al. 2005; Carey and Simnett 2006). On the other hand, several studies recognise that client-specific knowledge is lost when a partner changes off the audit and this can have an adverse impact on audit quality, largely due to lack of client-specific knowledge.[59] Therefore, there is still an ongoing debate regarding the relationship between audit partner change and audit quality. However, this stream of research mainly focuses on the association between audit partner change and the quality of statutory disclosures. To my knowledge, no prior studies have examined the relationship between audit partner change and the quality of non-statutory disclosures such as non-GAAP disclosures, which is the objective of this study.

This research examines whether the quality of voluntarily disclosed non-GAAP earnings varies when audit partner change occurs. Following prior studies, I measure the quality of non-GAAP earnings as the predictive ability of non-GAAP exclusions from statutory earnings for future operating performance (Doyle et al. 2003; Gu and Chen 2004; Kolev et al. 2008; Frankel et al. 2011). To

[58] Proponents of changing audit partner believe that new audit partners bring a fresh perspective to the audit, leading to more scepticism, greater auditor objectivity, and improved audit quality (Hamilton et al. 2005; Carey and Simnett 2006; Lennox et al. 2014).

[59] Chen et al. (2008) and Chi et al. (2009) argue that client-specific knowledge and experience, which can only be acquired over time with the client, are critically important for the audit partner to produce a higher quality audit. Therefore, the new audit partner might not possess client-specific knowledge and experience. For example, Chi et al. (2009) use Taiwanese data and find some evidence of reduced audit quality after a change of audit partners. Litt et al. (2014) use the change of audit firm to capture the effect of audit partner rotation in US firms, and report a lower degree of GAAP earnings quality after the change of auditor.

warrant their exclusions from statutory earnings, non-GAAP exclusions (measured as the difference between non-GAAP earnings and GAAP earnings) should be transitory without any predictive power for future performance (Kolev et al. 2008; Hsu and Kross 2011). Thus, "higher quality" non-GAAP exclusions are expected to be transitory, while "low-quality" exclusions tend to be permanent and have a significant association with future operating performance.

In particular, I consider whether disclosed non-GAAP earnings become more "conservative" when audit partner change occurs, where "conservative" non-GAAP earnings refer to a positive association between non-GAAP exclusions and future income, suggesting recurring gains are included in non-GAAP exclusions. In contrast, "aggressive" non-GAAP earnings refer to a negative association between non-GAAP exclusions and future incomes, implying the inclusion of recurring expenses among non-GAAP exclusions.

Ball et al. (2012) argue that audited financial reporting and voluntary disclosure are complementary mechanisms. Although non-GAAP earnings are beyond the statutory disclosure requirements, they are derived from statutory earnings after certain adjustments are made by managers. Therefore, to the extent that new audit partners prefer conservative accounting choices for statutory earnings as they are less familiar with their new clients and have more concerns over potential litigation costs (Kim et al. 2003), the disclosures of non-GAAP earnings would likely demonstrate a similar pattern and be relatively conservative. New audit partners are also more likely to identify cases where non-GAAP earnings numbers appear to be aggressive, particularly when they rely on non-

GAAP earnings metrics to set the materiality benchmark. While auditors do not comment publicly on non-GAAP information, they do report to the audit committee on whether the non-GAAP information is consistent with the audited financial statements (Black and Christensen 2018). Accordingly, new audit partners are more likely to raise concerns regarding the consistency and quality of non-GAAP earnings metrics with management and discuss with the audit committee and the board of directors. Managers, on the other hand, will consider this action as a form of threat and pressure (Turley and Zaman 2007). In equilibrium, managers become less likely to disclose aggressive non-GAAP earnings because of greater pressure from new audit partners.[60]

I estimate the implication of non-GAAP exclusions for future operating income by regressing future earnings on current non-GAAP earnings and non-GAAP exclusions. Using a sample of 2027 firm-year observations from 2002 to 2014 in Australia, the results demonstrate that a dollar of non-GAAP exclusions is associated with \$0.12 of future expenses for a client-firm without any change of audit partner. In contrast, when a client-firm has changed its audit partner, a dollar of non-GAAP exclusions is associated with \$0.12 of future incomes. In other words, non-GAAP exclusions reported by clients with new audit partners tend to contain recurring gains rather than recurring expenses, implying more conservative non-GAAP earnings disclosures than client-firms without a change of their audit partners. These results are robust to controlling for the effect of audit firm change.

[60] Alternatively, it can be argued that managers have more opportunity for opportunistic non-GAAP disclosures, since the new audit partner is less familiar with new clients (the effect of "knowledge learnings").

Next, I examine whether the quality of non-GAAP earnings varies accordingly to the prevalence of such disclosure across client-firm industries.[61] Given the disclosure of non-GAAP earnings numbers is voluntary and varies substantially across industries and firms, firms from industries where non-GAAP disclosures are prevalent would have more comparable benchmarks of non-GAAP earnings from their industry peers. The availability of comparable benchmarks may limit their ability and motivation to report aggressive non-GAAP earnings numbers since it increases the chance of being identified by market participants (Black et al. 2012; Doyle et al. 2013). On the other hand, firms from industries with a limited number of non-GAAP earnings disclosers would be better able to justify and provide relatively aggressive non-GAAP earnings figures without being detected and criticised by the market. Thus, I expect that the quality of non-GAAP earnings is higher in firms from industries where non-GAAP disclosure is relatively more prevalent. Consistent with the notion, I find supportive evidence that firms from prevalent industries are more likely to report higher quality non-GAAP earnings information than those from industries where non-GAAP disclosure is less common.

Given differences in the quality of non-GAAP earnings disclosure across client-firm industries, I further examine whether the association between audit partner change and the non-GAAP earnings quality is stronger in industries where non-GAAP disclosure is less prevalent. In the absence of comparable benchmarks of non-GAAP earnings from industry peers, new auditor partners may be more

[61] I classify companies into industries based on two-digit GICS codes. Following Coulton et al. (2016), I define non-GAAP prevalent industries as those most likely to present non-GAAP information, including Utilities, Consumer Discretionary, Financial and Industrial Classifications. Accordingly, I label industries, besides the above four industries, as less prevalent industries.

conservative when there is a material inconsistency between GAAP and non-GAAP earnings, particularly when the quality of non-GAAP earnings is relatively lower for client-firms from less prevalent industries. Thus. I conjecture that the change of a new audit partner may have a more significant impact on non-GAAP earnings quality among client-firms from industries where non-GAAP disclosure is less common. Consistent with this notion, I find that the positive association between audit partner change and non-GAAP earnings quality is more pronounced among client-firms from less prevalent industries. In contrast, the positive association is less significant for client-firms from industries where non-GAAP disclosure is more common, since the quality of non-GAAP earnings is relatively high for firms from these industries.

Finally, I examine whether the association between audit partner change and non-GAAP earnings quality varies across firms audited by Big 4 and non-Big 4 auditors and with different corporate governance mechanisms. The results suggest that the impact of audit partner change on non-GAAP earnings quality is more significant among Big 4 clients and those with weaker corporate governance environments as represented by lower board independence and smaller board size.

This research makes several important contributions to the literature on auditing, voluntary disclosure, and corporate governance. First, the prior research documents mixed evidence on the relationship between auditor change and audit quality (Hamilton et al. 2005; Carey and Simnett 2006; Chi et al. 2009; Cameran et al. 2013; Lennox et al. 2014; Litt et al. 2014; Laurion et al. 2017). Rather than focusing on the effect of audit partner change on the quality of statutory disclosures, this study examines the effect of audit partner change on the quality of a specific voluntary disclosure, namely the reporting of non-GAAP earnings. The results suggest that the change of audit partners improves the quality of non-statutory disclosures, and thus provides novel empirical evidence for the ongoing debate regarding audit partner change and the quality of auditing.

Second, this study contributes to the literature of voluntary disclosure by presenting a link between voluntary disclosures of non-GAAP numbers and audit partner changes. Given auditors' responsibilities for the quality of both statutory and non-statutory information presented in a firm's annual reports, the results in this study stress the important role played by external auditors in a firm's voluntary disclosure behaviour, particularly when the non-statutory financial information (non-GAAP earnings) is voluntarily disclosed together with its corresponding and comparable statutory information (GAAP earnings).

Finally, this study contributes to the broader corporate governance literature by providing further evidence on how the impact of external auditors on audit quality varies across different corporate governance environments. Although there is a large body of research examining the role of corporate governance environments in facilitating the monitoring of the quality of statutory (Klein 2002; Anderson et al. 2004) and non-statutory earnings (Frankel et al. 2011),[62] this study provides the first evidence on how the internal corporate governance environment influences the monitoring of the quality of voluntary disclosures by external auditors.

---

[62] Frankel et al. (2011) focus on the effect of the degree of board independence on the non-GAAP earnings quality. However, they do not consider any auditing effect.

This chapter is organised as follows. Section 4.2 presents a review of the literature and develops the research hypotheses. Research design, including sample construction, descriptive statistics, and correlation analysis, are discussed in Section 4.3. Section 4.4 discusses the results, and Section 4.5 concludes.

4.2 Literature review and hypothesis development

This section starts by considering the institutional background of audit partner change and relevant institutional detail regarding the role of auditors in assuring the quality of voluntary disclosure. It then reviews the association between audit partner change and financial reporting quality. Hypotheses about the association between audit partner change and non-GAAP earnings quality are then illustrated.

4.2.1 Institutional background

In Australia, the earliest references to audit partner change arose in a report issued by the professional accounting bodies (Australian Society of CPAs and The Institute of Chartered Accountants in Australia 1994) in 1994. In 2002, these professional accounting bodies jointly issued Professional Statement F1, which required their members to undertake audit partner change every seven years (Institute of Chartered Accountants in Australia and CPA Australia 2002)[63]. Subsequently, the Australian government passed the Corporate Law Economic

[63] The requirement was effective from 31 December, 2003 and followed the issue of a revised code of ethics by the International Federation of Accountants (IFAC) in 2001, which contained similar directions

Reform Program (Audit Reform and Corporate Disclosure) Act 2004 (CLERP 9) (Commonwealth of Australia 2004) to amend the Corporations Act 2001, to include the requirement for mandatory change of audit partners every five years[64]. The legislation states that an individual cannot play a significant role in the audit of a listed entity for more than five successive years or more than five out of seven successive years.[65] However, these individuals can resume a significant role in the audit after a cooling-off period of two years. Thus, the Australian rotation requirements are similar to those in the United States, which also require partner rotation after five years but with a cooling-off period of five years (U.S. House of Representatives 2002; Securities and Exchange Commission (SEC) 2003), but are stricter than the current European requirements of audit partner rotation after seven years (European Union 2006).

Chapple and Hossain (2011) compare the average partner tenure prior to and after the introduction of CLERP 9 legislation. They report that the average partner tenure was approximately three and a half years for their sample of Australian listed firms in the three years before the CLERP 9 requirements. In contrast, the average partner tenure in 2007 and 2008 fell to approximately two years. This suggests that voluntary rotation is widely practised before and after the introduction of the CLERP 9 legislation in Australia.

---

[64] The audit partner rotation requirements were effective from 1 July, 2006

[65] A significant role is that of the engagement partner and concurring or review partner.

4.2.2 Institutional details regarding auditors and non-GAAP disclosures

For many years, auditors have informally reviewed non-GAAP performance metrics disclosed in annual reports. In Australia, an auditor has responsibilities to ensure the quality of both statutory and non-statutory information included in an entity's annual reports. For example, auditing standard ASA 720 requires the auditor to read both financial and non-financial information, and consider whether there is a material inconsistency between the other information and the financial report.[66] "If the auditor identifies that a material inconsistency appears to exist (or becomes aware that the other information appears to be materially misstated), the auditor shall discuss the matter with management" (Para 16, ASA 720). Moreover, "if the auditor concludes that a material misstatement of the other information exists, the auditor shall request management to correct the other information" (Para 17, ASA 720). Since the non-GAAP earnings information is generally a component of the annual report, the auditor has responsibilities to ensure the sufficient quality of the non-GAAP earnings information.[67]

In addition, auditors often employ non-GAAP earnings as the materiality benchmark during the auditing process. When considering what benchmark to be used as a starting point in determining materiality, ASA 320 indicates that financial statement items and their volatility are important considerations (Para

[66] ASA 720 has been in effect since 2006, with an amendment in 2014. Prior to the adoption of the International Auditing Standards in 2005, Australian Auditing Standard (AUS) 212 Other Information in Documents Containing Audited Financial Reports have had similar requirements since 1995 (Para 11-17, AUS 212). Therefore, auditors' responsibility for statutory and non-statutory information appears similar throughout the sample period (2002–2014).

[67] Informal discussions with audit partners from all Big 4 firms confirm that audit partners read the non-GAAP earnings information included in annual reports and consider whether there is a material inconsistency between the non-GAAP earnings information and financial reports.

A3-A7, ASA320).[68] For example, “when, as a starting point, materiality for the financial report as a whole is determined for a particular entity based on a percentage of profit before tax from continuing operations, circumstances that give rise to an exceptional decrease or increase in such profit may lead the auditor to conclude that materiality for the financial report as a whole is more appropriately determined using a normalised profit before tax from continuing operations figure based on past results” (Para A6, ASA320). Non-GAAP earnings are typically found to be less volatile than GAAP earnings (Hallman et al. 2017). Therefore, if non-GAAP earnings serve as a higher quality measure of a firm’s underlying performance, then the use of non-GAAP earnings by auditors as the benchmark for determining the materiality amount would be prevalent and appropriate (Hallman et al. 2017). [69]

[68] ASA 320 has been in effect since 2006, with amendments in 2009 and 2011 respectively. Prior to the adoption of the International Auditing Standards, the relevant auditing standard is AUS306 Materiality and Audit Adjustments in 2001. AUS 306 states that “the auditor selects benchmark(s) appropriate to the entity’s circumstances for a quantitative evaluation of materiality at the financial report level and in relation to individual account balances, classes of transactions and disclosures. For example, an evaluation of materiality based on profit impact may not be appropriate when the entity is a not-for-profit organisation, or when the entity’s earnings are volatile.”

[69] Given that non-GAAP earnings have become a predominant financial metric disclosed by companies and is often touted as a more reliable and less volatile measure of recurring earnings, auditors may choose non-GAAP earnings as the materiality benchmark. Using the UK setting, Hallman et al. (2017) reveal that of the 229 companies that report non-GAAP profit-before-tax, auditors of 159 (69%) of these companies rely on non-GAAP profit-before-tax to set the materiality benchmark. Moreover, Eilifsen and Messier Jr (2015) show that seven of the eight largest US public accounting firms use income before income taxes or “normalised” earnings as the materiality benchmark. In Australia, the auditing standards do not require disclosure of the materiality threshold. However, in the discussions with Big 4 auditors, both auditors from PwC and Ernst and Young suggest that it is very common to use a non-GAAP measure in determining the materiality benchmark at the practical level.

4.2.3 Audit partner change and financial reporting quality

Archival research on audit partner change is limited because only a few jurisdictions require the name of the lead engagement partner to be disclosed.[70] Regulators believe that partner changes bring a fresh perspective to the audit and removes the familiarity threat that can lead to complacency (U.S. House of Representatives 2002). It can also improve actual and perceived independence, which tends to diminish with longer audit tenure (Carey and Simnett 2006; Daugherty et al. 2012). Furthermore, partner change is seen as a beneficial and less-costly alternative to audit firm change (Hamilton et al. 2005).

However, the literature in this area documents mixed evidence regarding the relationship between the change of audit partner and audit quality. Several studies have identified the potential benefits of the change of auditor by examining the tenure of audit partner and audit quality (Carey and Simnett 2006), while other studies directly investigate the relationship between audit partner change and audit quality. For example, using Australian data from 1998 to 2003, Hamilton et al. (2005) separately examine the association between the mandatory audit partner rotation and financial reporting quality for clients of Big 5 and non-Big 5 auditors. They find that the mandatory rotation of audit partners is associated with lower signed unexpected accruals, but find smaller and positive unexpected accruals following partner changes for Big 5 clients. They conclude that the change audit partner is associated with incrementally greater conservatism in financial reporting, but only in circumstances where the ability of client firms to resist

[70] Australia, China and Taiwan have this requirement. Recently, audit partners' name in the US have been publicly disclosed since 2017.

partner rotation is reduced by the mandatory requirement of partner rotation. In a recent study, Carson et al. (2014) examine the association between audit quality (measured by lower absolute discretionary accruals) and audit firm and audit partner changes for the period 2004–2011. They find some evidence of audit partner change being associated with lower discretionary accruals in the period 2004–2006, but the overall results suggest that audit firm changes have a stronger effect on audit quality than audit partner change. Lennox et al. (2014) test the impact of mandatory partner rotation on audit quality measured by audit adjustments among Chinese listed firms. They find that the mandatory rotation of engagement partner results in higher quality audits in the years immediately surrounding rotation. Overall, these studies find evidence that the new audit partner brings "fresh eyes" to accounting choices and disclosure policies of clients, thereby improving audit quality.

On the other hand, it is also recognised that client-specific knowledge is lost when a partner changes off the audit and this can have an adverse impact on audit quality (Manry et al. 2008; Bedard and Johnstone 2010; Daugherty et al. 2012; Litt et al. 2014). Particularly, there is a loss of "client-specific knowledge of risk, operations, and financial reporting practices in the initial years" (Chi et al. 2009, p.362). This loss of knowledge can increase the likelihood of audit failure. Pressure is placed on the incoming partner to obtain client-specific knowledge as quickly as possible even though continuity of the audit team helps to mitigate this loss. Evidence of negative audit quality outcomes due to audit partner change has been identified by applying measures that are more conducive to capture auditors' competence using Taiwanese data (Chi et al. 2009). Chi et al. (2009) find weak evidence of reduced audit quality, measured by discretionary accruals, and no evidence of improved shareholder perception relative to several benchmark samples. Bamber and Bamber (2009) comment that this may be due, in part, to the fact that mandatory auditor rotation in Taiwan can be superficial, where two signing partners are mandated but often only one is rotated. Manry et al. (2008) analyse proprietary data from actual audits in the US and find that partner tenure has no impact on audit quality measured by discretionary accruals for larger clients, or smaller clients with partner tenure being less than seven years. They further find that audit quality appears to improve with increased partner tenure for smaller clients with partner tenure longer than seven years. More recently, Litt et al. (2014) use the change of audit firm to capture the change of audit partner in the US setting. They claim that “clients that switch to new audit firms would have new audit partners beginning the year of change” (Litt et al. 2014, p.66), and find the lower financial reporting quality during the first two years with a new audit partner, compared with the final two years of tenure. Gipper et al. (2018) find no evidence for audit quality declines over the tenure cycle and, consistent with the former, little support for fresh-look benefits after five-year mandatory rotations. Nevertheless, Gipper et al. (2018) find increases in audit fees and decreases in audit hours over the tenure cycle, which differ by partner experience, client size, and competitiveness of the local audit market.

Overall, the evidence across various jurisdictions on whether audit partner change leads to higher disclosure quality remains inconclusive. On the one hand, longer tenure is associated with a lower propensity to issue going concerns opinions, indicating lower audit quality (Carey and Simnett 2006; Ye et al. 2011).

On the other hand, longer tenure is associated with smaller discretionary accruals, suggesting higher audit quality (Chen et al. 2008; Manry et al. 2008; Chi et al. 2017). Lennox and Wu (2017, p.10) suggest that "the different conclusions could be attributable to different institutional features of the jurisdictions examined, although it is not immediately obvious why the effects of tenure would be opposite in these two jurisdictions".

4.2.4 Hypotheses

As discussed previously, some studies find that a change of audit partner leads to an improvement in GAAP earnings quality (Hamilton et al. 2005; Lennox et al. 2014), while others suggest that a change of audit partner causes lower audit and earnings quality (Chen et al. 2008; Chi et al. 2009; Litt et al. 2014). The mixed evidence on audit partner changes may also be attributable to the variations in research settings used in prior studies. For example, Taiwan requires two audit partners to sign (Chen et al. 2008), where "fresh eyes" effect might be mitigated by the remaining partner. It is also unclear whether the remaining partner or the new partner plays a relatively more significant role on audit quality. Furthermore, Litt et al. (2014) use the change of audit firm to capture the change of audit partner in the US, as "clients that change audit firms will have a new audit partner beginning the year of change" (Litt et al. 2014, p.66). This measure for the change of audit partner can be noisy, as the impact of the change of audit firm is greater than the change of audit partner. The new audit firm will introduce and implement a new audit methodology, while the change of audit partner will not alter the audit approach (Bamber and Bamber 2009).

It is recognised that client-specific knowledge is lost when partner change occurs, while the new audit partner will bring “fresh eyes” to the accounting choices and disclosure policies of clients (Manry et al. 2008; Bedard and Johnstone 2010; Daugherty et al. 2012; Litt et al. 2014). Thus, I expect that new audit partners tend to be more conservative because they are less familiar with their new clients. Compared with the outgoing auditor, the new audit partner may have more concerns over potential litigation costs and prefer conservative (or income-decreasing) accounting choices, which in turn creates auditors’ incentives to monitor managers’ income-increasing accrual choices more closely than income-decreasing accrual choices (Kim et al. 2003).

Moreover, since auditors have legal responsibilities for the annual report as a whole including the disclosed non-GAAP information, auditors often use non-GAAP earnings metrics as the materiality benchmark (PricewaterhouseCoopers 2011; Eilifsen and Messier Jr 2015; Hallman et al. 2017). Although auditors do not report publicly on non-GAAP information, they need to report to the audit committee on whether the non-GAAP information is consistent with the audited financial statements (Black and Christensen 2018). Along this line, I conjecture that new audit partners are more likely to monitor non-GAAP earnings, particularly when the non-GAAP information is used to set the materiality benchmark. Thus, auditors might raise concerns regarding the quality of non-GAAP earnings information in the audit committee meeting, while the manager would consider this action as a form of threat and pressure (Turley and Zaman 2007). Due to the auditor's pressure on non-GAAP earnings quality, managers are likely to disclose more conservative non-GAAP earnings and aim to provide a better measure of underlying performance, consistent with their intention to inform shareholders and other stakeholders. In some cases, managers will even exclude transitory gains when disclosing non-GAAP earnings (Curtis et al. 2014). Based on the above discussions, I expect that the new audit partner would take a more conservative view of non-GAAP earnings numbers and place more pressure on managers, resulting in more conservative disclosures of non-GAAP earnings. The first hypothesis is expressed as follows:

H1: *Non-GAAP earnings are more conservative in the event of audit partner change.*

Given the disclosure of non-GAAP earnings numbers is voluntary and varies substantially across industries and firms, firms from industries where non-GAAP disclosures are prevalent would have more comparable benchmarks of non-GAAP earnings from their industry peers.[71] The availability of comparable benchmarks may limit their ability and motivation to report aggressive non-GAAP earnings numbers, since it increases the chance of being identified by market participants (Black et al. 2012; Doyle et al. 2013).[72] On the other hand, firms from industries with a limited number of non-GAAP earnings disclosers would be

[71] Firms in the same industry and fiscal year, and subject to the same general economic shocks, are expected to have a similar accruals and earnings structure (Francis et al. 2014).
[72] Both Black et al. (2012) and Doyle et al. (2013) find that market participants discount positive earnings surprises when accompanied by aggressive non-GAAP earnings, suggesting that the market partially understands the opportunistic nature of the aggressive non-GAAP earnings. It may reduce managers' incentives to report aggressive non-GAAP earnings numbers.

better able to justify and provide relatively aggressive non-GAAP earnings figures without being detected and criticised by the market. Therefore, I expect that the non-GAAP earnings quality is higher in firms from industries where non-GAAP disclosure is relatively more prevalent. This leads to the following hypothesis:

H2a: *Non-GAAP earnings quality is higher in firms from industries where non-GAAP disclosure is relatively more common.*

Next, this study considers whether the association between audit partner change and non-GAAP earnings quality is homogeneous across industries. As discussed previously, I expect that non-GAAP earnings quality is lower in client-firms from less prevalent industries. In the absence of comparable benchmarks of non-GAAP earnings from industry peers, audit partners with “fresh eyes” may have greater advantages, compared to the outfooting audit partners (Lennox and Wu 2017), in identifying cases where there is a material inconsistency between non-GAAP and GAAP earnings, thereby enhancing the quality of non-GAAP earnings numbers. In contrast, if the quality of non-GAAP is relatively high for firms from industries where non-GAAP disclosure is more prevalent (as predicted in H2a), new audit partners may have little impact on the quality of non-GAAP earnings reporting. Thus, I expect that audit partners with “fresh eyes” would play a more significant role in client-firms from industries where disclosure of non-GAAP is less prevalent. To compare the relationship between audit partner change and non-GAAP earnings quality across prevalent and less prevalent industries, the hypothesis is formulated as below:

H2b: *Non-GAAP earnings are more conservative in the event of audit partner change for firms from industries where non-GAAP disclosures are less prevalent than for those from prevalent disclosing industries.*

4.3. Research method and sample selection

4.3.1 Variable measurement

Audit partner change

I measure audit partner change as an indicator variable (*Audit Partner Change*). The partner change variable is defined as the firm-year in which an incoming partner, from the same audit firm as the outgoing partner, signs off on the client's audit report for the first time. I require both partners to reside at the same audit firm to eliminate instances of change due to audit firm switching.[73]

Non-GAAP earnings and exclusions

Following prior literature (Kolev et al. 2008; Frankel et al. 2011), non-GAAP exclusions (*Exclusions*) are defined as the difference between non-GAAP earnings (*Non_GAAP_Earnings*) and GAAP earnings (*GAAP_Earnings*): *Exclusions = Non_GAAP_Earnings– GAAP_Earnings*. When non-GAAP earnings are higher than GAAP earnings, *Exclusions* are positive, indicating that the average exclusion is an expense.

[73] Prior literature argues that there are some limitations for the identification of "new" partners. For example, Gipper et al. (2018) find that new partners can "shadow" the outgoing partner ahead of the audit partner change, including completing much of the partner hours on the audit.

Future operating income

The dependent variable is future operating income, defined as earnings per share from operations in t+1. I believe this dependent variable is best suited for examining the research questions because operating income excludes non-recurring special items but includes recurring items that might appear in firms' "other exclusions" from non-GAAP earnings. As such, it best approximates the concept of "permanent earnings". (Kolev et al. 2008; Frankel et al. 2011; Curtis et al. 2014).

Control variables

I include seven control variables in the main regression. Following prior literature (Doyle et al. 2003; Kolev et al. 2008; Frankel et al. 2011; Curtis et al. 2014), I include sales growth (*sg*), firm size (*sizeta*), earnings volatility (*voll12*), leverage (*lev*), an indicator variable for loss firms (*loss*) and the market-to-book ratio (*mtb*). Prior research documents that each of these variables are correlated with both non-GAAP earnings and future earnings (Doyle et al. 2003; Kolev et al. 2008; Frankel et al. 2011; Curtis et al. 2014). Also, I include an indicator variable for the use of a Big 4 auditor (*big4*), as I am examining the association between audit partner change and non-GAAP earnings quality and want to control for the effects of Big 4 auditors on non-GAAP earnings and future operating earnings.

Table 4.1 lists the definitions and measurement for all variables used in this study.

Table 4.1 Variable Measurement

Variable	Measurement
Panel A: Earnings variables	
GAAP_Earnings	*GAAP_Earnings* is GAAP earnings per share, calculated as the disclosed GAAP earnings together with non-GAAP earnings collected from a firm's earnings press release divided by the number of total shares outstanding
Non_GAAP_Earnings	*Non_GAAP_Earnings* is non-GAAP earnings per share, calculated as the non-GAAP earnings metric collected from earnings press release divided by the number of total shares outstanding
Exclusions	Exclusion is the difference between *Non_GAAP_Earnings* and *GAAP_Earnings* (*Exclusion=Non_GAAP_Earnings–GAAP_Earnings*)
Future Operating Income	*Future Operating Income* is earnings per share from operations in t+1
Panel B: Auditing variables	
Audit Partner Change	*Audit Partner Change* equals one if the audit partner change (within the audit firm) has occurred, and zero otherwise
Audit Firm Change	*Audit Firm Change* equals one if the audit firm change has occurred, and zero otherwise
Panel C: Firm's characteristics	
lev	Leverage is measured as (Total long-term debt + debt in current liabilities /Total assets
mtb	*mtb* is the market to book ratio, measured as the market value of equity divided by the book value of equity
sg	Sales growth equals sales in current year t minus sales in year t-1 divided by sales in year t-1
sizeta	Firm size is measured as the natural logarithm of total assets
loss	An indicator variable for loss firms equal one if GAAP earnings in year *t* is less than zero, and zero otherwise
big4	An indicator variable for the use of a Big 4 auditor equals one if the auditor is the Big 4 auditing firms, and zero otherwise
voll12	Earnings volatility is the standard deviation of return on assets (defined as net income divided by total assets) over the past 12 months
boardind	Board independence is measured as the number of independent directors on the board
boardsize	Board size is measured as the number of directors on the board

4.3.2 Sample selection

Non-GAAP earnings data for this study is hand-collected from earnings announcements for the Australian Securities Exchange (ASX) 500 firms from 2002 to 2014. Text search technology available from the Securities Industries Research Centre of Asia-Pacific (SIRCA) to identify all instances within full-year profit announcements, where a non-GAAP earnings measure was reported by the ASX 500 companies. The non-GAAP earnings data is identified and collected from firms' media releases, preliminary financial statements and annual reports using search terms such as "cash earnings", "core earnings", "underlying earnings" and "normalised profit".[74]

The final sample consists of 2027 firm-year observations for the period of 2002–2014. I use the ASPECT Huntleys FinAnalysis financial database to extract accounting information and the SIRCA database to extract auditing information. To mitigate the undue influence of outliers, I winsorise the top and bottom one percentile of key variables used in the regression analysis.[75]

4.3.3 Research method

I first hypothesise that the new audit partner prefers more conservative accounting choices and therefore places greater pressure on the manager. Thus, the manager would become more conservative with respect to non-GAAP exclusions. Following Kolev et al. (2008) and Frankel et al. (2011), I test the quality of non-

[74] A detailed summary of procedures for identifying and collecting non-GAAP disclosures is conducted by Coulton et al. (2016).
[75] Results remain unchanged when the regressions are run on the unwinsorised data.

GAAP earnings by regressing one-year-ahead operating income (*Future Operating Income*) on non-GAAP earnings, non-GAAP exclusions, the indicator variable of audit partner change, and the interactions terms. I also include time and industry fixed effect. In particular, I employ the following regression model to test the hypotheses:

$$\begin{aligned} \textit{Future Operating Income}_{t+1} = {} & \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{ Exclusions} + \beta_3 \textit{ Audit} \\ & \textit{Partner change} + \beta_4 \textit{ Non\_GAAP\_Earnings} \times \textit{Audit Partner Change} + \\ & \beta_5 \textit{ Exclusions} \times \textit{Audit Partner Change} + \gamma \textit{Controls}_i + \varepsilon_i \qquad (1) \end{aligned}$$

where *Future Operating Income* is earnings per share from operations in t+1; *Non_GAAP_Earnings* is earnings per share reported by management; *Exclusions* are the difference between non-GAAP and GAAP earnings; *Audit Partner Change* equals one if the audit partner change (within the audit firm) has occurred, and zero otherwise; *Controls* are control variables; ε is the error term.

Because all variables, except those indicator variables, are denominated in dollars per share and scaled by total assets per share, the coefficients in Model (1) can be interpreted as the future-dollar implication of a dollar change in the unscaled independent variable. If non-GAAP exclusions are irrelevant and non-recurring, and have no future earnings consequences, then the coefficient on non-GAAP exclusions in Model (1) (i.e., β_2) should be zero. Following the prior literature, I expect the coefficient on *Exclusions* to be negative, indicating that a portion of non-GAAP exclusions is recurring expenses (Doyle et al. 2003; Gu and Chen 2004; McVay 2006; Kolev et al. 2008; Frankel et al. 2011).

The estimated coefficient of interest in this regression is β_5. When the new audit partner imposes more pressure on the manager, the manager becomes more conservative about non-GAAP exclusions. I expect β_5 to be positive, countering the expected negative coefficient on *Exclusions*. More importantly, if the absolute value of β_5 is greater than the absolute value of β_2, it implies that the manager may exclude some gains when the audit partner change occurs, indicating conservative non-GAAP earnings.[76]

To examine whether non-GAAP earnings quality differs in industries with different degrees of non-GAAP disclosure prevalence, I estimate Equation (1) separately for industries classified as having a high propensity to disclose non-GAAP earnings and for all other industries after excluding the variable of audit partner change and its interactions terms. Accordingly, I test H2a using the following regression model:

$$Future\ Operating\ Income_{t+1} = \alpha + \beta_1 Non\_GAAP\_Earnings + \beta_2\ Exclusions + \gamma Controls_i + \varepsilon_i \quad (2)$$

The estimated coefficient of interest in this regression is β_2. I use a Wald test to compare β_2 estimated from prevalent industries and other industries. If the non-GAAP earnings quality is relatively higher in clients from prevalent industries, I expect the magnitude on β_2 to be relatively smaller for clients from prevalent industries than that for clients from less prevalent industries.

[76] An explanation for this result is that the exclusion of one-time gains decreases non-GAAP earnings, but provides a better depiction of core operating earnings relative to GAAP earnings (Curtis et al. 2014). Excluding transitory gains is an income-decreasing choice that the auditor prefers (Kim et al. 2003).

4.4 Results

4.4.1 Descriptive statistics and correlation analysis

Table 4.2 (Panel A) provides descriptive statistics on the key variables for the sample. The mean dollar value per share of GAAP earnings is 0.29, while the mean dollar value per share of non-GAAP earnings is 0.34. Consistently, the median value of non-GAAP earnings is also higher than that for GAAP earnings (0.20 vs. 0.16). These patterns reveal that non-GAAP earnings are systematically higher than GAAP earnings. Moreover, 18.2% of non-GAAP disclosers in the sample changed their audit partners during the period between 2002 and 2014,[77] while only 6.4% of them have changed their audit firms. The summary statistics also show that 84% of non-GAAP disclosers are audited by Big 4 auditors.[78]

Panel B shows the number of audit partner changes that occurred among non-GAAP disclosers for each of the years. There are 368 partner changes among non-GAAP disclosers during the 13-year period. Consistent with prior literature (Stewart et al. 2016), the highest percentage (32%) of audit partner changes occurred in 2007, the first year of mandatory rotation in Australia. Among non-

[77] Using data from Australia, Stewart et al. (2016) document that about 23% of their sample changed audit partner in the period between 2007 and 2010.

[78] In an international study, Francis et al. (2013) find that in 2,335 firm-year observations in Australia between 1997 and 2007, 71% of firms are audited by Big 4 auditors, while the Big 4 audit market Herfindahl index based on is 0.46.

GAAP disclosers, the results demonstrate that Big 4 clients are more likely to change audit partner (19%) than non-Big 4 clients (12%).[79]

[79] Hamilton et al. (2005) find that about 16% of their sample has rotated audit partner. They also find that Big 5 clients are more likely to change their audit partners (19%) than non-Big 5 clients (10%).

Table 4.2 Summary Statistics

The sample contains a maximum 2027 firm-year observations from 2002 to 2014. All variables have been winsorised at percentile bands one and ninety-nine, and are defined in Table 4.1.

Panel A: Summary statistics

Variable	Mean	Std Dev	Q1	Median	Q3	min	max
Future Operating Income	0.288	0.443	0.045	0.169	0.389	-0.697	2.297
Non_GAAP_Earnings	0.339	0.448	0.085	0.195	0.416	-0.194	2.777
GAAP_Earnings	0.287	0.512	0.039	0.157	0.370	-1.094	3.070
Exclusions	0.052	0.272	-0.003	0.021	0.092	-2.262	2.838
Audit Partner Change	0.182	0.386	0.000	0.000	0.000	0.000	1.000
Audit Firm Change	0.064	0.245	0.000	0.000	0.000	0.000	1.000
lev	0.236	0.169	0.110	0.228	0.335	0.000	0.880
mtb	2.410	2.856	1.021	1.650	2.703	0.121	25.170
sg	0.471	4.258	-0.040	0.065	0.226	-0.966	120.889
sizeta	20.504	1.663	19.316	20.529	21.829	15.276	23.153
loss	0.097	0.296	0.000	0.000	0.000	0.000	1.000
big4	0.840	0.367	1.000	1.000	1.000	0.000	1.000
voll12	0.102	0.063	0.060	0.085	0.125	0.021	0.534

Table 4.2 (continued)

Panel B: Audit partner change by year and auditor type

	Full sample			**Big 4 sub-sample**			**Non-Big 4 sub-sample**		
	Number of Change	Non-GAAP Disclosers	Percentage	Number of Change	Non-GAAP Disclosers	Percentage	Number of Change	Non-GAAP Disclosers	Percentage
2002	18	93	19%	17	83	20%	1	10	10%
2003	15	108	14%	15	98	15%	0	10	0%
2004	16	120	13%	15	105	14%	1	15	7%
2005	26	141	18%	22	123	18%	4	18	22%
2006	21	148	14%	19	132	14%	2	16	13%
2007	50	155	32%	47	129	36%	3	26	12%
2008	30	181	17%	26	145	18%	4	36	11%
2009	33	173	19%	27	143	19%	6	30	20%
2010	25	172	15%	21	143	15%	4	29	14%
2011	33	173	19%	29	139	21%	4	34	12%
2012	39	164	24%	37	136	27%	2	28	7%
2013	26	181	14%	25	153	16%	1	28	4%
2014	36	218	17%	30	173	17%	6	45	13%
Total	**368**	**2027**	**18%**	**330**	**1702**	**19%**	**38**	**325**	**12%**

Table 4.3 reports Pearson and Spearman correlations for the key variables used in the regression analyses. All variables, except financial leverage, are significantly correlated at the 10% significance level to the dependent variable of the regression analyses, namely *Future Operating Income* in Pearson (Spearman) correlations. As expected, non-GAAP exclusions are negatively associated with *Future Operating Income*. Consistent with the prior literature, these results show that non-GAAP exclusions are less persistent than non-GAAP earnings (0.059<0.772), with a portion of non-GAAP exclusions being recurring expenses (Doyle et al. 2003; Gu and Chen 2004; McVay 2006; Kolev et al. 2008; Frankel et al. 2011).

Table 4.3 Correlation Coefficients

Variable	*Future Operating Income*	*Non_GAAP_Earnings*	*Exclusions*	*Audit Partner Change*	*Audit Firm Change*	*lev*	*mtb*	*sg*	*sizeta*	*loss*	*voll12*	*big4*
Future Operating Income	1.000	0.761*	-0.075*	0.075*	-0.079*	0.111*	0.372*	0.084*	0.427*	-0.393*	-0.412*	0.220*
	.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Non_GAAP_Earnings	0.772*	1.000	0.024	0.081*	-0.101*	0.178*	0.344*	0.071*	0.537*	-0.460*	-0.479*	0.230*
	0.00	.	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Exclusions	-0.059*	0.002	1.000	0.031	0.012	0.115*	-0.097*	-0.120*	0.076*	0.068*	0.094*	0.064*
	0.01	0.94	.	0.17	0.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Audit Partner Change	0.062*	0.075*	0.001	1.000	-0.099*	-0.002	0.021	0.018	0.081*	-0.053*	-0.047*	0.136*
	0.01	0.00	0.98	.	0.00	0.93	0.36	0.42	0.00	0.02	0.04	0.00
Audit Firm Change	-0.054*	-0.068*	0.005	-0.099*	1.000	0.002	-0.056*	-0.006	-0.052*	0.029	0.093*	-0.064*
	0.02	0.00	0.82	0.00	.	0.94	0.01	0.78	0.02	0.20	0.00	0.00
lev	0.016	0.022	0.073*	-0.011	-0.002	1.000	-0.010	-0.025	0.366*	-0.184*	-0.178*	0.080*
	0.48	0.33	0.00	0.64	0.92	.	0.67	0.28	0.00	0.00	0.00	0.00
mtb	0.202*	0.194*	-0.028	0.011	-0.042*	0.013	1.000	0.211*	-0.019	-0.180*	-0.235*	0.058*
	0.00	0.00	0.22	0.63	0.06	0.55	.	0.00	0.40	0.00	0.00	0.01
sg	-0.054*	-0.065*	-0.028	0.017	-0.011	-0.049*	0.015	1.000	-0.077*	-0.124*	-0.019	-0.161*
	0.02	0.00	0.21	0.45	0.63	0.03	0.51	.	0.00	0.00	0.39	0.00
sizeta	0.378*	0.438*	0.029	0.086*	-0.042*	0.358*	-0.096*	-0.087*	1.000	-0.322*	-0.368*	0.325*
	0.00	0.00	0.19	0.00	0.06	0.00	0.00	0.00	.	0.00	0.00	0.00
loss	-0.253*	-0.255*	0.085*	-0.053*	0.029	-0.164*	-0.052*	0.108*	-0.365*	1.000	0.338*	-0.177*
	0.00	0.00	0.00	0.02	0.20	0.00	0.02	0.00	0.00	.	0.00	0.00
voll12	-0.272*	-0.299*	0.097*	-0.044*	0.081*	-0.153*	-0.069*	0.160*	-0.364*	0.393*	1.000	-0.163*
	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	.	0.00
big4	0.178*	0.169*	0.015	0.136*	-0.064*	0.056*	0.018	-0.101*	0.341*	-0.177*	-0.200*	1.000
	0.00	0.00	0.50	0.00	0.00	0.01	0.44	0.00	0.00	0.00	0.00	.

This table presents the correlation matrix for the selected variables used in the analysis. The sample consists of 2,027 firm-year observations between 2002 and 2014. Pearson (Spearman) correlation coefficients are in the lower (upper) triangle.
*significant at the 10% level.

4.4.2 Audit partner change and non-GAAP earnings quality

For tests of the relationship between audit partner change and non-GAAP earnings quality, I regress one-year-ahead operating income (*Future Operating Income*) on non-GAAP earnings, non-GAAP exclusions, and the indicator variable for audit partner change; and their interactions terms. The results reported in Table 4.4 show that the coefficient on exclusions (β_2) is -0.116 (t =-2.28). Consistent with prior research, non-GAAP exclusions (β_2) are less persistent than non-GAAP earnings (β_1) (0.116<0.847), but they are not entirely transitory (Doyle et al. 2003; Gu and Chen 2004; Frankel et al. 2011). The coefficient on the interaction term between non-GAAP exclusions and audit partner change is positive (β_5 =0.240) and significant (t =2.93). More importantly, the magnitude of β_5 is greater than that for β_2 (0.240>0.116). The results indicate that one dollar of non-GAAP exclusions is associated with \$0.12 (0.240-0.116) gains in the future among firms that have changed their audit partners, compared with \$0.12 expenses in the future for those without audit partner change. Overall, the results support H1 and suggest that the disclosed non-GAAP exclusions are more conservative when audit partner change occurs because the exclusions include some gains and less recurring expenses items (Curtis et al. 2014).

Some control variables have significant coefficients and signs consistent with prior research. For example, the indicator of loss firm (*loss*) is negatively associated (β= -0.085, t =-2.76) with the future operating income (*Future Operating Income*), suggesting that loss firms have lower future operating income. On the other hand, the market-to-book ratio (*mtb*) is positively associated (β=

0.012, t =3.29) with the future operating income, indicating firms with higher market-to-book ratio have higher future operating income (Kolev et al. 2008; Curtis et al. 2014).

Table 4.4 Audit Partner Change and Non-GAAP Earnings Quality

This table examines the association between Non-GAAP earnings quality and audit partner changes using the following regression model:

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{Exclusions} + \beta_3 \textit{Audit Partner Change} + \beta_4 \textit{Non\_GAAP\_Earnings} \times \textit{Audit Partner Change} + \beta_5 \textit{Exclusions} \times \textit{Audit Partner Change} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Audit Partner Change* equals one if the audit partner change (within audit firm) has occurred, and zero otherwise; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firms (*loss*), earnings volatility (*voll12*), and an indicator variable for Big 4 auditors (*big4*), ε is the error term. Figures in parentheses are *t*-statistics. *** (**, *) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 4.1.

VARIABLES	(1) *Future Operating Income*
Constant	-0.153
	(-0.82)
Non_GAAP_Earnings	0.847***
	(16.27)
Exclusions	**-0.116****
	(-2.28)
Audit Partner Change	0.015
	(0.55)
Non_GAAP_Earnings×Audit Partner Change	-0.086
	(-0.96)
Exclusions×Audit Partner Change	**0.240****
	(2.93)
lev	-0.057
	(-0.99)
mtb	0.012**
	(3.29)
sg	0.000
	(0.92)
sizeta	0.013
	(1.51)
loss	-0.085**
	(-2.76)
voll12	0.126
	(0.64)
big4	0.003
	(0.25)
Industry Dummy	Yes
Year Dummy	Yes
Observations	1,581
Adjusted R-squared	0.618
Wald Test	*Exclusions+Exclusions×Audit Partner Change* =0
P-value	0.078

4.4.3 Non-GAAP earnings quality: Prevalence of non-GAAP earnings disclosures

Next, I test whether the non-GAAP earnings quality differs in clients from industries with different degree of non-GAAP disclosure prevalence, In Table 4.5, I divide the sample into two groups, namely industries where non-GAAP disclosures are prevalent and those where they are less prevalent. Based on a detailed survey of Australian non-GAAP disclosures (Coulton et al. 2016), I consider the prevalent industries are those most likely to present non-GAAP information, including Utilities, Consumer Discretionary, Financial and Industrial sectors.[80] Column (1) reports the result for the quality of non-GAAP earnings in clients from prevalent industries, while Column (2) presents the results for clients from less prevalent industries. The results show that non-GAAP exclusions of clients from less prevalent (β_2 =-0.157, t =-2.71) industries are negatively associated with future operating earnings. This is consistent with prior literature, and indicates that a portion of non-GAAP exclusions is recurring expenses (Doyle et al. 2003; Gu and Chen 2004; McVay 2006; Kolev et al. 2008; Frankel et al. 2011).

On the other hand, non-GAAP exclusions of clients from prevalent industries are not significantly associated with the future operating earnings. Importantly, the result from the between equations test for *Exclusions* (β_2) reveals that non-GAAP exclusions of clients from prevalent industries are significantly (p-value =0.028) lower than non-GAAP exclusions of clients from less prevalent

[80] Coulton et al. (2016) find that the percentage of non-GAAP disclosers is: Utilities (50%), Consumer Discretionary (39.2%), Financial (41.4%) and Industrial (35.3%) respectively. These sectors are most likely to present non-GAAP information from 2000 to 2014 inclusive, which is primarily aligned with the sample period (2001–2014).

industries. Supporting H2a, these results demonstrate that the quality of non-GAAP earning is relatively higher among clients from industries where non-GAAP disclosure is more prevalent.

Table 4.5 Non-GAAP Earnings Quality: Prevalence of Non-GAAP Earnings Disclosures

This table examines whether the non-GAAP earnings quality differs in clients from industries with different degrees of non-GAAP disclosure prevalence using Model (2):

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{ Exclusions} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firms (*loss*), an indicator for Big auditors and volatility of returns (*voll12*), ε is the error term. Figures in parentheses are *t*-statistics. *** (**,*) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 4.1. *Prevalent industries* are those most likely to present non-GAAP information, including Utilities, Consumer Discretionary, Financial and Industrial Classifications (Coulton et al. 2016).

	Prevalent	**Less prevalent**
VARIABLES	(1) *Future Operating Income*	(2) *Future Operating Income*
Constant	-0.641*	-0.362
	(-2.74)	(-0.80)
Non_GAAP_Earnings	0.752***	0.781***
	(17.69)	(22.07)
Exclusions	-0.027	**-0.157****
	(-1.15)	**(-2.71)**
lev	-0.243**	-0.040
	(-3.67)	(-0.44)
mtb	0.019***	0.021*
	(10.23)	(2.50)
sg	-0.011	0.000
	(-1.36)	(0.97)
sizeta	0.039*	0.017
	(2.82)	(0.76)
loss	-0.048*	-0.133**
	(-2.50)	(-2.93)
voll12	-0.640**	-0.001
	(-4.24)	(-0.00)
big4	-0.052	0.041
	(-1.43)	(0.87)
Industry Dummy	Yes	Yes
Year Dummy	Yes	Yes
Observations	927	786
Adjusted R-squared	0.551	0.605
Between equations test	(1) vs (2)	
$\boldsymbol{\beta_2}$ (P-value)	0.028	

4.4.4 Audit partner change and non-GAAP earnings quality: Prevalence of non-GAAP earnings disclosure

I next examine whether the prevalence of non-GAAP disclosures is associated with differences in the association between audit partner change and non-GAAP earnings quality. In Table 4.6, I divide the sample into two groups, namely prevalent and less prevalent industries. The results for prevalent industries are reported in Column (1), while Column (2) presents results for less prevalent industries. The results show that the coefficients on *Exclusions* continue to be negative and significant (β_2 =-0.107, t =-2.63 for prevalent industries; and β_2 =-0.111, t =-2.03 for less prevalent industries respectively). On the other hand, the coefficients on *Exclusions*×*Audit Partner Change* are positive (β_5 =0.185, t =1.87 for prevalent industries; and β_5 =0.256, t =2.98 for less prevalent industries respectively), with a larger magnitude than those for *Exclusions*, implying clients tend to report more conservative non-GAAP earnings when the audit partner change occurs. More importantly, β_5 is higher in less prevalent industries, compared with prevalent industries (0.256 >0.185), indicating that the change of audit partner has a more significant impact on the quality of non-GAAP earnings in firms from less prevalent industries than those from prevalent industries.

Overall, the results in Table 4.6 show that the association between audit partner change and non-GAAP quality persist for client-firms from both prevalent and less prevalent industries. However, the impact of audit partner change on non-GAAP earnings quality is more pronounced for client-firms from industries where non-GAAP disclosures are less common.

Table 4.6 Audit Partner Change and Non-GAAP Earnings Quality: Prevalence of Non-GAAP Earnings Disclosure

This table examines the association between Non-GAAP earnings quality and audit partner changes using the following regression model:

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{Exclusions} + \beta_3 \textit{Audit Partner Change} + \beta_4 \textit{Non\_GAAP\_Earnings} \times \textit{Audit Partner Change} + \beta_5 \textit{Exclusions} \times \textit{Audit Partner Change} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Audit Partner Change* equals one if the audit partner change (within audit firm) has occurred, and zero otherwise; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firms (*loss*), earnings volatility (*voll12*), and an indicator for Big 4 auditors (*big4*), ε is the error term. Figures in parentheses are *t*-statistics. *** (**, *) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 4.1.

	Prevalent	**Less prevalent**
	(1)	(2)
VARIABLES	*Future Operating Income*	*Future Operating Income*
Constant	-0.168	-0.114
	(-1.37)	(-0.51)
Non_GAAP_Earnings	0.923***	0.779***
	(31.32)	(14.97)
Exclusions	**-0.107****	**-0.111***
	(-2.63)	**(-2.03)**
Audit Partner Change	0.051	-0.012
	(1.66)	(-0.36)
Non_GAAP_Earnings×Audit Partner Change	-0.199	-0.009
	(-1.59)	(-0.13)
Exclusions×Audit Partner Change	**0.185***	**0.256****
	(1.87)	**(2.98)**
lev	-0.091	-0.005
	(-1.84)	(-0.04)
mtb	0.012**	0.016**
	(2.67)	(2.84)
sg	0.002	0.000
	(1.16)	(0.09)
sizeta	0.009	0.009
	(1.25)	(0.80)
loss	-0.018	-0.118**
	(-0.65)	(-2.97)
voll12	-0.088	-0.002
	(-0.90)	(-0.01)
big4	-0.016	0.066***
	(-1.00)	(3.91)
Industry Dummy	Yes	Yes
Year Dummy	Yes	Yes
Observations	869	712
Adjusted R-squared	0.632	0.597
Wald Test	*Exclusions+Exclusions×Audit Partner Change*=0	*Exclusions+Exclusions×Audit Partner Change*=0
P-value	0.463	0.072

4.4.5 Audit partner change and non-GAAP earnings quality: The role of the corporate governance environment

I also investigate whether the relationship between audit partner change and non-GAAP earnings quality varies across client-firms with different corporate governance environments. I focus on two governance attributes, namely board independence and board size. Prior studies generally suggest that a highly independent board of directors leads to a better governance environment, as board independence is found to be positively associated with financial reporting quality and the performance of firms (Klein 2002; Farber 2005; Krishnan 2005). Specifically, the prior literature suggests that firms with highly independent boards of directors are more likely to report higher quality of non-GAAP earnings, compared with those with relatively less independent directors (Frankel et al. 2011). However, the empirical evidence on the association between board size and financial reporting quality is mixed. On the one hand, larger firms with larger board size are more likely to allow better distribution of workload and committee assignments, leading to more effective board decisions, enhanced corporate governance and improved financial reporting quality (Laksmana 2008). On the other hand, larger boards can be less effective monitors because of the potential free-riding problem, poor communication and inefficient decision making (Dechow et al. 1996a; Bushman et al. 2004).

To examine the extent to which corporate governance mechanisms influence the association between audit partner change and non-GAAP earnings quality, I divide the sample into two groups, based on the median value of each corporate governance attribute respectively. The results reported in Panel A of Table 4.7 show that, for client-firms with relatively more independent boards, the coefficient on *Exclusions*×*Audit Partner Change* is positive but insignificant (β_5 =0.096, t =1.51). In contrast, this coefficient is positive (β_5 =0.162) and significant (t =3.23) for client-firms with relatively less independent boards of directors.

The results for board size are reported in Panel B. I find that non-GAAP earnings numbers are more conservative when audit partner changes occur in client-firms with relatively smaller boards of directors (β_5 =0.344, t =3.92), while the association is insignificant for client-firms with relatively large boards. In all, the results suggest that when audit partner change occur in client-firms with relatively lower independence and smaller board, non-GAAP earnings tend to be more conservative.

Table 4.7 Audit Partner Change and Non-GAAP Earnings Quality: The Role of Corporate Governance Environment

This table examines the association between Non-GAAP earnings quality and audit partner changes using the following regression model:

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{Exclusions} + \beta_3 \textit{Audit Partner Change} + \beta_4 \textit{Non\_GAAP\_Earnings} \times \textit{Audit Partner Change} + \beta_5 \textit{Exclusions} \times \textit{Audit Partner Change} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Audit Partner Change* equals one if the audit partner change (within audit firm) has occurred, and zero otherwise; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator variable for loss firms (*loss*), earnings volatility (*voll12*) and an indicator for Big 4 auditors (*big4*), ε is the error term. Figures in parentheses are *t*-statistics. *** (**,*) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 4.1

Panel A: Board Independence	**High**	**Low**
	(1)	(2)
VARIABLES	*Future Operating Income*	*Future Operating Income*
Constant	-0.062	-0.541**
	(-0.18)	(-2.41)
Non_GAAP_Earnings	0.901***	0.820***
	(11.96)	(17.82)
Exclusions	-0.099	-0.013
	(-1.72)	(-0.31)
Audit Partner Change	0.054	-0.032**
	(1.22)	(-2.73)
Non_GAAP_Earnings×Audit Partner Change	-0.287***	0.206***
	(-3.65)	(3.91)
Exclusions×Audit Partner Change	0.096	**0.162****
	(1.51)	**(3.23)**
lev	-0.142	-0.015
	(-1.39)	(-0.17)
mtb	0.008*	0.019***
	(2.33)	(6.47)
sg	-0.002	0.001**
	(-1.20)	(2.56)
sizeta	0.007	0.028*
	(0.38)	(2.20)
loss	-0.109***	-0.010
	(-4.16)	(-0.76)
vol12	0.114	0.013
	(0.58)	(0.11)
big4	0.013	-0.032**
	(0.40)	(-2.82)
Industry Dummy	Yes	Yes
Year Dummy	Yes	Yes
Observations	827	709
Adjusted R-squared	0.632	0.674
Wald Test	*Exclusions+Exclusions×Audit Partner Change =0*	*Exclusions+Exclusions×Audit Partner Change =0*
P-value	0.966	0.000

Panel B: Board Size	**Large**	**Small**
	(1)	(2)
VARIABLES	*Future Operating Income*	*Future Operating Income*
Constant	0.031	-0.719**
	(0.15)	(-2.63)
Non_GAAP_Earnings	0.877***	0.865***
	(20.83)	(22.79)
Exclusions	-0.028	**-0.113****
	(-0.84)	**(-2.98)**
Audit Partner Change	0.051	-0.009
	(1.62)	(-0.34)
Non_GAAP_Earnings×Audit Partner Change	-0.124	-0.093
	(-1.33)	(-0.67)
Exclusions×Audit Partner Change	0.131	**0.344*****
	(1.79)	**(3.92)**
lev	-0.066	-0.043
	(-1.02)	(-0.53)
mtb	0.014***	0.009**
	(4.08)	(2.69)
sg	-0.001*	0.001**
	(-2.12)	(2.39)
sizeta	0.007	0.039**
	(0.77)	(2.67)
loss	-0.069	-0.044***
	(-1.55)	(-3.59)
vol12	-0.098	0.416**
	(-0.48)	(3.07)
big4	-0.031*	-0.006
	(-1.91)	(-0.38)
Industry Dummy	Yes	Yes
Year Dummy	Yes	Yes
Observations	904	634
Adjusted R-squared	0.659	0.551
Wald Test	*Exclusions+Exclusions×Audit Partner Change =0*	*Exclusions+Exclusions×Audit Partner Change =0*
P-value	0.217	0.031

4.4.6 Audit partner change and non-GAAP earnings quality: The role of Big 4 auditors

I also examine the effect of hiring Big 4 auditors on the relationship between audit partner change and the quality of non-GAAP earnings. Prior studies show that hiring one of the Big 4 auditors can improve a firm's financial reporting quality (Francis et al. 1999; Dechow and Dichev 2002; Doyle et al. 2007). Big 4 auditors are generally more competent and independent than non-Big 4 audit firms, because they invest heavily in auditor training and facilitator programs, and have a large portfolio of clients (Khurana and Raman 2004). In addition, auditing theory suggests that Big 4 auditors are of higher quality because of the higher risk to their reputation (DeAngelo 1981; Skinner and Srinivasan 2012) and higher litigation risk (Dye 1993; Khurana and Raman 2004). In contrast, a small auditor with fewer clients and less wealth at risk of litigation tends to have higher incentives to "satisfy" its clients in order to retain them. Furthermore, because Big 4 auditors are larger, they tend to have a greater capacity to incur the fixed-cost investment in audit programs and in-house rules (Francis et al. 2014). Therefore, I expect that Big 4 auditors have better auditing modules and procedures, resulting in higher non-GAAP earnings quality.

To control for the brand name, I repeat the tests on the sample of firms audited by Big 4 auditors. The results in Table 4.8 show that the positive association between audit partner change and non-GAAP earnings quality remain unchanged among Big 4 clients. For example, the coefficient on *Exclusions* is negative and significant (β_2 =-0.059, t =-2.09), suggesting that non-GAAP exclusions have some predictive ability for future operating earnings, even for firms who are clients of Big 4 auditors. Furthermore, the coefficient on *Exclusions*×*Audit Partner Change* is positive and significant (β_5 =0.177, t =2.43). Consistent with the results reported in Table 4.4, these results suggest that managers tend to report more conservative non-GAAP earnings numbers when the audit partner change occurs in Big 4 clients.

Table 4.8 Audit Partner Change and Non-GAAP Earnings Quality: The Role of Big 4 Auditors

This table examines the association between non-GAAP earnings quality and audit partner changes using the following regression model:

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{Exclusions} + \beta_3 \textit{Audit Partner Change} + \beta_4 \textit{Non\_GAAP\_Earnings} \times \textit{Audit Partner Change} + \beta_5 \textit{Exclusions} \times \textit{Audit Partner Change} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Audit Partner Change* equals one if audit partner change (within audit firm) has occurred, and zero otherwise; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firm (*loss*), earnings volatility (*voll12*) and an indicator variable for Big 4 auditors (*big4*), *ε* is the error term. Figures in parentheses are *t*-statistics. *** (**,*) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 4.1

VARIABLES	(1) *Future Operating Income*
Constant	-0.260
	(-1.10)
Non_GAAP_Earnings	0.878***
	(27.49)
Exclusions	**-0.059****
	(-2.09)
Audit Partner Change	0.026
	(1.12)
Non_GAAP_Earnings×Audit Partner Change	-0.101
	(-1.43)
Exclusions×Audit Partner Change	**0.177****
	(2.43)
lev	-0.092**
	(-2.31)
mtb	0.009*
	(1.92)
sg	0.001**
	(2.55)
sizeta	0.015
	(1.40)
loss	-0.071**
	(-2.48)
voll12	0.026
	(0.12)
Industry Dummy	Yes
Year Dummy	Yes
Observations	1,349
Adjusted R-squared	0.631
Wald Test	*Exclusions+Exclusions×Audit Partner Change* =0
P-value	0.163

4.4.7 Audit partner change and non-GAAP earnings quality: Controlling audit firm change

Finally, I test the robustness of the relationship between audit partner change and the quality of non-GAAP earnings numbers by controlling for any change in audit firm. Audit firm change is a costly alternative to audit partner change (Hamilton et al. 2005), while potentially achieving a similar objective of encouraging a fresh approach to the audit (Stewart et al. 2016). While results reported in Table 4.4 suggest that the disclosed non-GAAP earnings are more conservative in the event of audit partner change, one question is whether the quality of non-GAAP would be further improved or attenuated if the client changes its audit firm. Chen et al. (2008, p.420) point out that "audit firm tenure could be attributable to partner tenure (or vice versa) because these two measures of tenure are correlated with each other". Thus, it is important to understand whether the relation between audit partner change and the quality of non-GAAP earnings is attributable to the effect of audit firm change.

To address this concern, I augment Model (1) by including the audit firm change (*Audit Firm Change*), and two interactions terms, namely *Non_GAAP_Earnings×Audit Firm Change*, and *Exclusions×Audit Firm Change*. The results reported in Table 4.9 show that the coefficient on *Exclusions* is negative and significant (β_2 =-0.112, t =-2.00), while the coefficient on *Exclusions×Audit Partner Change* is positive and significant (β_5 = 0.236, t= 2.69). This suggests that a dollar of non-GAAP exclusions is associated with \$0.12 (0.236-0.112) gains in the future when audit partner change occurs, compared with \$0.11 future expenses for those that do not change their audit partners. Importantly, the coefficient on *Exclusions×Audit Firm Change* is negative but insignificant, suggesting that the audit firm change has no significant impact on the quality of non-GAAP earnings. In summary, these results confirm that non-GAAP earnings tend to be conservative when audit partner change occurs, while the change of audit firm does not lead to a similar effect on non-GAAP earnings numbers. The results also highlight the importance of audit partner change, which imposes a different and significant effect on influencing the quality of non-GAAP earnings disclosures compared with the change of audit firms.

Table 4.9 Audit Partner Change and Non-GAAP Earnings Quality: Controlling Audit Firm Change

This table examines the association between non-GAAP earnings quality and audit partner changes after controlling the audit firm change effect using the following regression models:

$$\textit{Future Operating Income}_{t+1} = \alpha + \beta_1 \textit{Non\_GAAP\_Earnings} + \beta_2 \textit{Exclusions} + \beta_3 \textit{Audit Partner Change} + \beta_4 \textit{Non\_GAAP\_Earnings} \times \textit{Audit Partner Change} + \beta_5 \textit{Exclusions} \times \textit{Audit Partner Change} + \beta_6 \textit{Audit Firm Change} + \beta_7 \textit{Non\_GAAP\_Earnings} \times \textit{Audit Firm Change} + \beta_8 \textit{Exclusions} \times \textit{Audit Firm Change} + \gamma \textit{Controls}_i + \varepsilon_i$$

where *Future Operating Income* is earnings per share from operations, *Non_GAAP_Earnings* is earnings per share reported by the management, *Exclusions* is non-GAAP earnings less GAAP earnings, *Audit Partner Change* equals one if audit partner change (within audit firm) has occurred, and zero otherwise; Audit Firm Change (*Audit Firm Change)* equals one if the client has changed its audit firm, and zero otherwise; *Controls* includes leverage (*lev*), the market to book ratio (*mtb*), sales growth rate (*sg*), firm size (*sizeta*), an indicator for loss firms (*loss*), earnings volatility (*voll12*) and an indicator variable of Big 4 auditors (*big4*), ε is the error term. Figures in parentheses are *t*-statistics. *** (**, *) indicates significant at the 1% (5%, 10%) level for two-tailed test. All variables are defined in Table 4.1.

VARIABLES	(1) *Future Operating Income*
Constant	-0.157
	(-0.83)
Non_GAAP_Earnings	0.845***
	(16.00)
Exclusions	**-0.112***
	(-2.00)
Audit Partner Change	0.015
	(0.54)
Non_GAAP_Earnings×Audit Partner Change	-0.084
	(-0.94)
Exclusions×Audit Partner Change	**0.236****
	(2.69)
Audit Firm Change	0.004
	(0.10)
Non_GAAP_Earnings×Audit Firm Change	0.008
	(0.11)
Exclusions×Audit Firm Change	-0.128
	(-0.44)
lev	-0.056
	(-0.96)
mtb	0.012**
	(3.24)
sg	0.000
	(0.94)
sizeta	0.013
	(1.49)
loss	-0.084**
	(-2.80)
vol12	0.129
	(0.66)
big4	0.003
	(0.23)
Industry Dummy	Yes
Year Dummy	Yes
Observations	1,581
Adjusted R-squared	0.622
Wald Test	*Exclusions+Exclusions×Audit Partner Change* =0
P-value	0.080

4.5 Conclusions

Non-GAAP earnings disclosures are increasingly more prevalent. Although the non-GAAP earnings disclosure is beyond the requirements of statutory disclosures and considered as a form of voluntary disclosure, non-GAAP earnings numbers are derived directly from statutory earnings figures. In addition, the auditing standards require auditors to consider whether there is any significant difference between statutory and non-statutory earnings included in annual reports. Non-GAAP earnings are often used as the materiality benchmark in the auditing procedure.

Using a sample of ASX 500 firms with hand-collected non-GAAP earnings data over 2002–2014, the results in this study suggest that non-GAAP earnings are more conservative when a change of audit partners occurs. Further, I also find that non-GAAP earnings quality is relatively higher in clients from industries where non-GAAP disclosure is prevalent. In particular, the empirical evidence also indicates that the impact of audit partner change on the quality of non-GAAP earnings is relatively more significant in clients from less prevalent industries, or with less effective corporate governance environments.

Overall, these results support the view that the new audit partner can improve disclosure quality by bringing “fresh eyes” on the accounting choices and disclosure policies of clients. Beyond controlling for the effect of audit firm changes, this essay does not attempt to separately to identify possible instances of partner rotation as distinct from other reasons for partners no longer continuing (e.g., retirement). Audit partner change effects documented in this essay take no account of whether the partner change is due to a rotation policy (mandatory or voluntary) or other sources and circumstances. In conclusion, the results of this study provide important insights for auditors, regulators, and investors into the possible benefits of mandatory audit partner change in terms of improving the quality of voluntary disclosures.

Chapter Five: Conclusion

This dissertation examines three specific issues regarding financial reporting quality and auditor attributes. In Chapter Two, I illustrate how commonly-used unexpected accruals measures reduce the type I error rate by sacrificing the type II error rate. Since accounting information users and auditors typically face much higher costs with respect to type II errors, I explicitly identify why unexpected accruals models are likely far less useful in detecting earnings overstatements than a relatively simple approach using financial statement analysis red flags. The results highlight the fundamentally contrasting incentives facing accounting researchers relative to those who might otherwise use the results from empirical research in practice, and serve as a warning when the broader relevance of accounting research is increasingly under question.

In Chapter Three, I examine the impact of industry-specialist auditors on the quality of non-GAAP earnings. I find that non-GAAP exclusions tend to have less predictive ability for future operating earnings in firms audited by industry-specialist auditors, suggesting a higher degree of non-GAAP earnings quality. These results reveal that industry-specialist auditors can improve the quality of voluntary disclosure beyond mandatory disclosures required by accounting standards. In addition, the results suggest that clients from industries where non-GAAP disclosure is prevalent are more likely to have higher non-GAAP earnings quality, compared with those from less prevalent industries. Importantly, the results of this study also show a positive association between industry-specialist auditors and the quality of non-GAAP disclosures in clients from industries where non-GAAP disclosures are less prevalent, which is not evident among firms from prevalent industries. The findings suggest that industry-specialist auditors are less important among industries where non-GAAP disclosures are prevalent, since the non-GAAP quality is already high among firms in those industries.

Chapter Four considers whether audit partner change influences the quality of non-GAAP earnings voluntarily disclosed by firms. The results show that non-GAAP exclusions tend to be more conservative in clients with new audit partners. Furthermore, the positive association between audit partner change and the quality of non-GAAP disclosures is more pronounced among clients from less prevalent industries, suggesting that the association between new audit partners play a more important role in influencing the quality of non-GAAP earnings in those industries. I also find that non-GAAP earnings are more conservative when audit partner change occurs among Big 4 clients or clients with relatively lower board independence and smaller board size.

In conclusion, this dissertation responds to the long-term debate over fundamental concerns regarding the relevance of accounting research. It then extends extant research examining auditor effect on financial reporting quality to a broader area by investigating how the voluntary disclosures quality is influenced by two important attributes of auditors. These essays enhance our understanding of how accounting research should be conducted and the impacts of auditors on the quality of voluntary disclosures.

Reference

Anderson, R. C., S. A. Mansi, and D. M. Reeb. 2004. Board characteristics, accounting report integrity, and the cost of debt. *Journal of Accounting and Economics* 37 (3):315-342.

Armstrong, C. S., A. D. Jagolinzer, and D. F. Larcker. 2010. Chief executive officer equity incentives and accounting irregularities. *Journal of Accounting Research* 48 (2):225-271.

Audousset-Coulier, S., A. Jeny, and L. Jiang. 2016. The validity of auditor industry specialization measures. *Auditing: A Journal of Practice & Theory* 35 (1):139-161.

Australian Society of CPAs and The Institute of Chartered Accountants in Australia. 1994. A Research Study on Financial Reporting and Auditing—Bridging the Expectation Gap. Melbourne, Australia: Australian Society of CPAs.

Ball, R. 2013. Accounting informs investors and earnings management is rife: Two questionable beliefs. *Accounting Horizons* 27 (4):847-853.

Ball, R., S. Jayaraman, and L. Shivakumar. 2012. Audited financial reporting and voluntary disclosure as complements: A test of the confirmation hypothesis. *Journal of Accounting and Economics* 53 (1-2):136-166.

Balsam, S., J. Krishnan, and J. S. Yang. 2003. Auditor industry specialization and earnings quality. *Auditing: A Journal of Practice & Theory* 22 (2):71-97.

Bamber, E. M., and L. S. Bamber. 2009. Discussion of" Mandatory Audit Partner Rotation, Audit Quality, and Market Perception: Evidence from Taiwan". *Contemporary Accounting Research* 26 (2):393-402.

Beaver, W. H., and M. F. McNichols. 1998. The characteristics and valuation of loss reserves of property casualty insurers. *Review of Accounting Studies* 3 (1-2):73-95.

Bedard, J. C., and K. M. Johnstone. 2010. Audit partner tenure and audit planning and pricing. *Auditing: A Journal of Practice & Theory* 29 (2):45-70.

Beneish, M. D. 1999. The detection of earnings manipulation. *Financial Analysts Journal* 55 (5):24-36.

Bhattacharya, N., E. L. Black, T. E. Christensen, and R. D. Mergenthaler. 2004. Empirical evidence on recent trends in pro forma reporting. *Accounting Horizons* 18 (1):27-43.

Black, D. E., E. L. Black, and T. E. Christensen. 2014. The effects of executive compensation contracts and auditor effort on pro forma reporting decisions. *available at SSRN 1312562*.

Black, D. E., E. L. Black, T. E. Christensen, and W. G. Heninger. 2012. Has the regulation of pro forma reporting in the US changed investors' perceptions of pro forma earnings disclosures? *Journal of Business Finance & Accounting* 39 (7-8):876-904.

Black, D. E., and T. E. Christensen. 2009. US managers' use of 'pro forma'adjustments to meet strategic earnings targets. *Journal of Business Finance & Accounting* 36 (3-4):297-326.

Black, D. E., and T. E. Christensen. 2018. Policy Implications of Research on Non-GAAP Reporting. *Forthcoming, Research in Accounting Regulation*.

Bowen, R. M., A. K. Davis, and S. Rajgopal. 2002. Determinants of Revenue-Reporting Practices for Internet Firms. *Contemporary Accounting Research* 19 (4):523-562.

Burnett, B.M., C.M. Bradrick, G. W. Martin, and B. P. McAllister. 2012 Audit Quality and the Trade-Off between Accretive Stock Repurchases and Accrual-Based Earnings Management. *The Accounting Review* 87 (6):1861-1884.

Bushman, R., Q. Chen, E. Engel, and A. Smith. 2004. Financial accounting information, organizational complexity and corporate governance systems. *Journal of Accounting and Economics* 37 (2):167-201.

Cameran, M., J. R. Francis, A. Marra, and A. Pettinicchio. 2013. Are there adverse consequences of mandatory auditor rotation? Evidence from the Italian experience. *Auditing: A Journal of Practice & Theory* 34 (1):1-24.

Carey, P., and R. Simnett. 2006. Audit partner tenure and audit quality. *The Accounting Review* 81 (3):653-676.

Carson, E., R. Simnett, B. S. Soo, and A. M. Wright. 2012. Changes in audit market competition and the Big N premium. *Auditing: A Journal of Practice & Theory* 31 (3):47-73.

Chapple, L., and S. Hossain. 2011. Mandatory auditor rotation: Australian evidence. *Australian Journal of Corporate Law* 25:303-317.

Chen, C. Y., C. J. Lin, and Y. C. Lin. 2008. Audit Partner Tenure, Audit Firm Tenure, and Discretionary Accruals: Does Long Auditor Tenure Impair Earnings Quality?. *Contemporary Accounting Research* 25 (2):415-445.

Chen, L., G. Krishnan, and M. Pevzner. 2012. Pro forma disclosures, audit fees, and auditor resignations. *Journal of Accounting and Public Policy* 31 (3):237-257.

Chi, W., H. Huang, Y. Liao, and H. Xie. 2009. Mandatory Audit Partner Rotation, Audit Quality, and Market Perception: Evidence from Taiwan. *Contemporary Accounting Research* 26 (2):359-391.

Chi, W., L. A. Myers, T. C. Omer, and H. Xie. 2017. The effects of audit partner pre-client and client-specific experience on audit quality and on perceptions of audit quality. *Review of Accounting Studies* 22 (1):361-391.

Collins, D. W., R. S. Pungaliya, and A. M. Vijh. 2017. The effects of firm growth and model specification choices on tests of earnings management in quarterly settings. *The Accounting Review* 92 (2):69-100.

Commonwealth of Australia. 2004. Corporate Law Economic Reform Program (Audit Reform and Corporate Disclosure) Act 2004. (CLERP 9). Canberra, Australia Commonwealth of Australia.

Coulton, J., A. Ribeiro, Y. Shan, and S. Taylor. 2016. The Rise and Rise of Non-GAAP Disclosure: A survey of Australian practice and its implications. Sydney, Australia: Chartered Accountants Australia and New Zealand.

Craswell, A. T., J. R. Francis, and S. L. Taylor. 1995. Auditor brand name reputations and industry specializations. *Journal of Accounting and Economics* 20 (3):297-322.

Curtis, A. B., S. E. McVay, and B. C. Whipple. 2014. The disclosure of non-GAAP earnings information in the presence of transitory gains. *The Accounting Review* 89 (3):933-958.

Daugherty, B. E., D. Dickins, R. C. Hatfield, and J. L. Higgs. 2012. An examination of partner perceptions of partner rotation: Direct and indirect consequences to audit quality. *Auditing: A Journal of Practice & Theory* 31 (1):97-114.

Davis, A. K. 2002. The Value Relevance of Revenue for Internet Firms: Does Reporting Grossed-up or Barter Revenue Make a Difference? *Journal of Accounting Research* 40 (2):445-477.

DeAngelo, L. E. 1981. Auditor size and audit quality. *Journal of Accounting and Economics* 3 (3):183-199.

Dechow, P., W. Ge, and C. Schrand. 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics* 50 (2-3):344-401.

Dechow, P. M., and I. D. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (s-1):35-59.

Dechow, P. M., W. Ge, C. R. Larson, and R. G. Sloan. 2011. Predicting material accounting misstatements. *Contemporary Accounting Research* 28 (1):17-82.

Dechow, P. M., A. P. Hutton, J. H. Kim, and R. G. Sloan. 2012. Detecting earnings management: A new approach. *Journal of Accounting Research* 50 (2):275-334.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1995. Detecting earnings management. *The Accounting Review* 70 (2):193-225.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1996a. Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC. *Contemporary Accounting Research* 13 (1):1-36.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1996b. Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the sec. *Contemporary Accounting Research* 13 (1):1-36.

DeFond, M., and J. Zhang. 2014. A review of archival auditing research. *Journal of Accounting and Economics* 58 (2):275-326.

DeFond, M. L., J. R. Francis, and T. J. Wong. 2000. Auditor industry specialization and market segmentation: Evidence from Hong Kong. *Auditing: A Journal of Practice & Theory* 19 (1):49-66.

DeFond, M. L., C. Lennox, and J. Zhang. 2018. The Primacy of Fair Presentation: Evidence from Regulators and the Courts. *Accounting Horizons* Forthcoming.

Dopuch, N., and D. Simunic. 1982. Competition in auditing: An assessment. Paper read at Fourth Symposium on auditing research.

Doyle, J. T., W. Ge, and S. McVay. 2007. Accruals quality and internal control over financial reporting. *The Accounting Review* 82 (5):1141-1170.

Doyle, J. T., J. N. Jennings, and M. T. Soliman. 2013. Do managers define non-GAAP earnings to meet or beat analyst forecasts? *Journal of Accounting and Economics* 56 (1):40-56.

Doyle, J. T., R. J. Lundholm, and M. T. Soliman. 2003. The predictive value of expenses excluded from pro forma earnings. *Review of Accounting Studies* 8 (2):145-174.

Dunn, K. A., and B. W. Mayhew. 2004. Audit firm industry specialization and client disclosure quality. *Review of Accounting Studies* 9 (1):35-58.

Dyckman, T. R., and S. A. Zeff. 2015. Accounting research: past, present, and future. *Abacus* 51 (4):511-524.

Dye, R. A. 1993. Auditing standards, legal liability, and auditor wealth. *Journal of Political Economy* 101 (5):887-914.

Eilifsen, A., and W. F. Messier Jr. 2015. Materiality guidance of the major public accounting firms. *Auditing: A Journal of Practice & Theory* 34 (2):3-26.

Entwistle, G. M., G. D. Feltham, and C. Mbagwu. 2005. The voluntary disclosure of pro forma earnings: a US-Canada comparison. *Journal of International Accounting Research* 4 (2):1-23.

European Union. 2006. 8th Directive on Company Law. 2006/43/EC. Brussels, Belgium: European Commission.

Farber, D. B. 2005. Restoring trust after fraud: Does corporate governance matter? *The Accounting Review* 80 (2):539-561.

Fargher, N., H.-Y. Lee, and V. Mande. 2008. The effect of audit partner tenure on client managers' accounting discretion. *Managerial Auditing Journal* 23 (2):161-186.

Ferguson, A., J. R. Francis, and D. J. Stokes. 2003. The effects of firm-wide and office-level industry expertise on audit pricing. *The Accounting Review* 78 (2):429-448.

Ferguson, A., and D. Stokes. 2002. Brand Name Audit Pricing, Industry Specialization, and Leadership Premiums post-Big 8 and Big 6 Mergers. *Contemporary Accounting Research* 19 (1):77-110.

Feroz, E. H., K. Park, and V. S. Pastena. 1991. The financial and market effects of the SEC's accounting and auditing enforcement releases. *Journal of Accounting Research* 29 (Supplement):107-142.

Fields, T. D., T. Z. Lys, and L. Vincent. 2001. Empirical research on accounting choice. *Journal of Accounting and Economics* 31 (1-3):255-307.

Files, R. 2012. SEC enforcement: Does forthright disclosure and cooperation really matter? *Journal of Accounting and Economics* 53 (1-2):353-374.

Firth, M. A., O. M. Rui, and X. Wu. 2012. Rotate back or not after mandatory audit partner rotation? *Journal of Accounting and Public Policy* 31 (4):356-373.

Francis, J. R., E. L. Maydew, and H. C. Sparks. 1999. The role of Big 6 auditors in the credible reporting of accruals. *Auditing: A Journal of Practice & Theory* 18 (2):17-34.

Francis, J. R., P. N. Michas, and S. E. Seavey. 2013. Does audit market concentration harm the quality of audited earnings? Evidence from audit markets in 42 countries. *Contemporary Accounting Research* 30 (1):325-355.

Francis, J. R., M. L. Pinnuck, and O. Watanabe. 2014. Auditor style and financial statement comparability. *The Accounting Review* 89 (2):605-633.

Frankel, R., S. McVay, and M. Soliman. 2011. Non-GAAP earnings and board independence. *Review of Accounting Studies* 16 (4):719-744.

Gipper, B., L. Hail, and C. Leuz. 2018. On the Economics of Audit Partner Tenure and Rotation: Evidence from PCAOB Data. *Stanford University Graduate School of Business Research Paper No. 17-56*

Gerakos, J. 2012. Discussion of detecting earnings management: A new approach. *Journal of Accounting Research* 50 (2):335-347.

Gu, Z., and T. Chen. 2004. Analysts' treatment of nonrecurring items in street earnings. *Journal of Accounting and Economics* 38:129-170.

Habib, A. 2011. Audit firm industry specialization and audit outcomes: Insights from academic literature. *Research in Accounting Regulation* 23 (2):114-129.

Hallman, N. J., J. J. Schmidt, and A. M. Thompson. 2017. Auditor use of non-GAAP earnings when setting quantitative materiality. In *International Symposium on Audit Research*. Sydney Australia

Hamilton, J., C. Ruddock, D. J. Stokes, and S. L. Taylor. 2005. Audit partner rotation, earnings quality and earnings conservatism. *Working paper, University of New South Wales*.

Hay, D. 2013. Further evidence from meta-analysis of audit fee research. *International Journal of Auditing* 17 (2):162-176.

Hay, D. C., W. R. Knechel, and N. Wong. 2006. Audit fees: A Meta-analysis of the effect of supply and demand attributes. *Contemporary Accounting Research* 23 (1):141-191.

He, W., B. Sidhu, and S. L. Taylor. 2017. Audit Quality and Properties of Analysts' Information Environment. *Working Paper University of Technology Sydney.*

Heckman, J. J. 1979. Sample selection bias as a specification error. *Econometrica: Journal of the econometric society* 37:153-161.

Heflin, F., and C. Hsu. 2008. The impact of the SEC's regulation of non-GAAP disclosures. *Journal of Accounting and Economics* 46 (2-3):349-365.

Hoang, K., S. E. Salterio, and J. Sylph. 2017. Barriers to transferring accounting and auditing research to standard setters. In *International Symposium on Audit Research*. Sydney.

Hoogervorst, H. 2016. Performance reporting and the pitfalls of non-GAAP metrics. Annual Conference of the European Accounting Association, Maastricht Netherlands.

Hopwood, A. G. 2007. Whither accounting research? *The Accounting Review* 82 (5):1365-1374.

Hsu, C., and W. Kross. 2011. The Market Pricing of Special Items that are Included in versus Excluded from Street Earnings. *Contemporary Accounting Research* 28 (3):990-1017.

Institute of Chartered Accountants in Australia and CPA Australia. 2002. Code of Professional Conduct: Professional Independence. Professional Statement F1. Sydney, Australia Institute of Chartered Accountants in Australia and CPA Australia.

Jansen, I. P., S. Ramnath, and T. L. Yohn. 2012. A diagnostic for earnings management using changes in asset turnover and profit margin. *Contemporary Accounting Research* 29 (1):221-251.

Jones, J. J. 1991. Earnings management during import relief investigations. *Journal of Accounting Research* 29 (2):193-228.

Kaplan, R. S. 2011. Accounting scholarship that advances professional knowledge and practice. *The Accounting Review* 86 (2):367-383.

Khurana, I. K., and K. Raman. 2004. Litigation risk and the financial reporting credibility of Big 4 versus non-Big 4 audits: Evidence from Anglo-American countries. *The Accounting Review* 79 (2):473-495.

Kim, J. B., R. Chung, and M. Firth. 2003. Auditor conservatism, asymmetric monitoring, and earnings management. *Contemporary Accounting Research* 20 (2):323-359.

Klein, A. 2002. Audit committee, board of director characteristics, and earnings management. *Journal of Accounting and Economics* 33 (3):375-400.

Knechel, R. W., A. Vanstraelen, and M. Zerni. 2015. Does the identity of engagement partners matter? An analysis of audit partner reporting decisions. *Contemporary Accounting Research* 32 (4):1443-1478.

Knechel, W. R., V. Naiker, and G. Pacheco. 2007. Does auditor industry specialization matter? Evidence from market reaction to auditor switches. *Auditing: A Journal of Practice & Theory* 26 (1):19-45.

Knechel, W. R., and S. E. Salterio. 2016. *Auditing: Assurance and risk*: Taylor & Francis.

Kolev, K., C. A. Marquardt, and S. E. McVay. 2008. SEC scrutiny and the evolution of non-GAAP reporting. *The Accounting Review* 83 (1):157-184.

Kothari, S. P., A. J. Leone, and C. E. Wasley. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39 (1):163-197.

Krishnan, J. 2005. Audit committee quality and internal control: An empirical analysis. *The Accounting Review* 80 (2):649-675.

Laksmana, I. 2008. Corporate board governance and voluntary disclosure of executive compensation practices. *Contemporary Accounting Research* 25 (4):1147-1182.

Laurion, H., A. Lawrence, and J. P. Ryans. 2017. US audit partner rotations. *The Accounting Review* 92 (3):209-237.

Lawrence, A., M. Minutti-Meza, and P. Zhang. 2011. Can Big 4 versus non-Big 4 differences in audit-quality proxies be attributed to client characteristics? *The Accounting Review* 86 (1):259-286.

Lennox, C., and X. Wu. 2017. A Review of the Archival Literature on Audit Partners. *Accounting Horizons* Forthcoming.

Lennox, C. S., J. R. Francis, and Z. Wang. 2012. Selection models in accounting research. *The Accounting Review* 87 (2):589-616.

Lennox, C. S., X. Wu, and T. Zhang. 2014. Does mandatory rotation of audit partners improve audit quality? *The Accounting Review* 89 (5):1775-1803.

Li, X., and H. I. Yang. 2016. Mandatory financial reporting and voluntary disclosure: The effect of mandatory IFRS adoption on management forecasts. *The Accounting Review* 91 (3):933-953.

Lim, C. Y., and H. T. Tan. 2008. Non-audit service fees and audit quality: The impact of auditor specialization. *Journal of Accounting Research* 46 (1):199-246.

Litt, B., D. Sharma, T. Simpson, and P. N. Tanyi. 2014. Audit Partner Rotation and Financial Reporting Quality. *Auditing: A Journal of Practice & Theory*.

Liu, X., and D. A. Simunic. 2005. Profit sharing in an auditing oligopoly. *The Accounting Review* 80 (2):677-702.

Manry, D. L., T. J. Mock, and J. L. Turner. 2008. Does increased audit partner tenure reduce audit quality? *Journal of Accounting, Auditing & Finance* 23 (4):553-572.

Marquardt, C. A., and C. I. Wiedman. 2004. How are earnings managed? An examination of specific accruals. *Contemporary Accounting Research* 21 (2):461-491.

Mayhew, B. W., and M. S. Wilkins. 2003. Audit firm industry specialization as a differentiation strategy: Evidence from fees charged to firms going public. *Auditing: A Journal of Practice & Theory* 22 (2):33-52.

McNichols, M. 2002. Discussion of the quality of accruals and earnings: multiples. *Journal of Accounting Research* 40 (1):135-172.

McVay, S. E. 2006. Earnings management using classification shifting: An examination of core earnings and special items. *The Accounting Review* 81 (3):501-531.

Melumad, N. D., and D. Nissim. 2009. Line-item analysis of earnings quality. *Foundations and Trends in Accounting* 3 (2–3):87-221.

Miller, G. S., and D. J. Skinner. 1998. Determinants of the valuation allowance for deferred tax assets under SFAS No. 109. *Accounting Review* 73 (2):213-233.

Minutti-Meza, M. 2013. Does auditor industry specialization improve audit quality? *Journal of Accounting Research* 51 (4):779-817.

Moehrle, S. R., K. L. Anderson, F. L. Ayres, C. E. Bolt-Lee, R. S. Debreceny, M. T. Dugan, C. E. Hogan, M. W. Maher, and E. Plummer. 2009. The impact of academic accounting research on professional practice: An analysis by the AAA Research Impact Task Force. *Accounting Horizons* 23 (4):411.

Nelson, M. W., J. A. Elliott, and R. L. Tarpley. 2002. Evidence from auditors about managers' and auditors' earnings management decisions. *The Accounting Review* 77 (s-1):175-202.

Ohlson, J. A. 2015. Accounting research and common sense. *Abacus* 51 (4):525-535.

Owens, E. L., J. S. Wu, and J. Zimmerman. 2017. Idiosyncratic shocks to firm underlying economics and abnormal accruals. *The Accounting Review* 92 (2):183-219.

Payne, J. L. 2008. The influence of audit firm specialization on analysts' forecast errors. *Auditing: A Journal of Practice & Theory* 27 (2):109-136.

Petroni, K. R. 1992. Optimistic reporting in the property-casualty insurance industry. *Journal of Accounting and Economics* 15 (4):485-508.

PricewaterhouseCoopers. 2011. Materiality in audits. Australia.

Rasmussen, S. J. 2013. Revenue recognition, earnings management, and earnings informativeness in the semiconductor industry. *Accounting Horizons* 27 (1):91-112.

Reichelt, K. J., and D. Wang. 2010. National and office-specific measures of auditor industry expertise and effects on audit quality. *Journal of Accounting Research* 48 (3):647-686.

Ribeiro, A., Y. Shan, and S. Taylor. 2018. Non-GAAP Earnings and the Earnings Quality Trade-off. *Working Paper, University of Technology Sydney*.

Roychowdhury, S. 2006. Earnings management through real activities manipulation. *Journal of Accounting and Economics* 42 (3):335-370.

Schilit, H. 2010. *Financial shenanigans*: Tata McGraw-Hill Education.

Schrand, C. M., and S. L. Zechman. 2012. Executive overconfidence and the slippery slope to financial misreporting. *Journal of Accounting and Economics* 53 (1-2):311-329.

Securities and Exchange Commission (SEC). 2003. Strengthening the Commission's Requirements Regarding Auditor Independence. Final Rule. Rel. No. 33-8183, File No.: S7-49-02.

Sheskin, D. 2003. *The Handbook of Parametric and Nonparametric Statistical Procedures: Third Edition*. Boca Raton, FL: Chapman and Hall/CRC.

Skinner, D. J., and S. Srinivasan. 2012. Audit quality and auditor reputation: Evidence from Japan. *The Accounting Review* 87 (5):1737-1765.

Stewart, J., P. Kent, and J. Routledge. 2016. The association between audit partner rotation and audit fees: Empirical evidence from the Australian market. *Auditing: A Journal of Practice & Theory* 35 (1):181-197.

Stubben, S. R. 2010. Discretionary revenues as a measure of earnings management. *The Accounting Review* 85 (2):695-717.

Summers, S. L., and J. T. Sweeney. 1998. Fraudulently misstated financial statements and insider trading: An empirical analysis. *The Accounting Review* 73 (1):131-146.

Teoh, S. H., T. J. Wong, and G. R. Rao. 1998. Are accruals during initial public offerings opportunistic? *Review of Accounting Studies* 3 (1-2):175-208.

Turley, S., and M. Zaman. 2007. Audit committee effectiveness: informal processes and behavioural effects. *Accounting, Auditing & Accountability Journal* 20 (5):765-788.

U.S. House of Representatives 2002. The Sarbanes-Oxley Act of 2002. Public Law 107-204 [H. R. 3763]. Washington. D.C.

Ye, P., E. Carson, and R. Simnett. 2011. Threats to auditor independence: The impact of relationship and economic bonds. *Auditing: A Journal of Practice & Theory* 30 (1):121-148.

Zang, A. Y. 2011. Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review* 87 (2):675-703.

Zhang, H., and L. Zheng. 2011. The valuation impact of reconciling pro forma earnings to GAAP earnings. *Journal of Accounting and Economics* 51 (1-2):186-202.

Appendix 2.1: Abnormal sales index measure

Net Revenue† is a notional estimate of non-manipulated net revenue. It seeks to measure the effect of manipulation that specifically results from opportunistic distortions in the timing of its recognition. This is determined by analysing the time series change in the ratio of receivables-to-sales.

To begin, revenue should be recognised in the period that it is *earned*. However, the derivation of revenue is often a continuous process and ascertaining an appropriate point at which it is *earned* is difficult to determine and requires some subjective judgment. This subjective judgment facilitates the use opportunistic manipulation. Outlined subsequently is a set of mathematical formulas to derive *Net Revenue*†.

To determine current non-manipulated net revenue (Net Revenue†), reported revenue must be reduced by the amount by which it is overstated. This requirement can be mathematically expressed as

$$\text{Net Revenue}^{\dagger} = \text{Sales Revenue} - \Delta S$$

where *Net Revenue*† equals revenue before the effect of prematurely recognised credit sales, *Sales Revenue* is the amount reported in financial statements, and ΔS is the dollar volume of overstated revenue. Due to the fixed accounting relations that tie the balance sheet to the profit and loss statement, any intervention in the timing of credit sales will be accrued on the balance sheet, namely the accounts receivable balance. In essence, Net Revenue overstatements resulting from expedited credit transactions are simultaneously and uniformly reflected as overstatements in accounts receivables. Hence, the overstatement in sales revenue can be expressed as:

$$\Delta S = \Delta R$$

where ΔR is the dollar value of overstated receivables. The amount of aggressively accrued receivables can also be expressed as:

$$\Delta R = \text{Accounts Receivable} - \text{Accounts Receivable}^{\dagger}$$

where *Accounts Receivable* is the amount reported in the financial statements, and *Accounts Receivable*† is the dollar amount of non-manipulated receivables. To estimate a value for *Accounts Receivable*†, several assumptions need to be made. Typically, timing manipulation that seeks to capture premature sales transactions is detected from time series increases in the ratio of receivables to sales. Assuming last year's ratio is a clean/non-manipulated ratio, *Accounts Receivable*† can be expressed as:

$$\text{Accounts Receivable}^{\dagger} = (\text{Accounts Receivable}_{t-1} / \text{Net Revenue}_{t-1}) * \text{Net Revenue}^{\dagger}$$

These mathematical relations provide the basis for a simultaneous equation approach to detecting and estimating the magnitude of revenue manipulation. The accuracy of the model is dependent on the extent to which revenue manipulation is observed and reflected in changes in the ratio of receivables to sales. Putting all these equations together and solving for *Net Revenue*† gives

$$\text{Net Revenue}^{\dagger} = \text{Sales Revenue}_{t} - [\text{Accounts Receivable}_{t} - ((\text{Accounts Receivable}_{t-1} / \text{Net Revenue}_{t-1}) * \text{Net Revenue}_{t}^{\dagger})]$$

$$\text{Net Revenue}^{\dagger} = \frac{\text{Net Revenue}_t - \text{Accounts Receivable}_t}{(1 - \text{Accounts Receivable}_{t-1} / \text{Net Revenue}_{t-1})}$$

Appendix 3.1: Relevant Australian auditing standards

ASA 320: Materiality in Planning and Performing an Audit

Para A4: Determining materiality involves the exercise of professional judgement. A percentage is often applied to a chosen benchmark as a starting point in determining materiality for the financial report as a whole. Factors that may affect the identification of an appropriate benchmark include the following:

- The elements of the financial report (for example, assets, liabilities, equity, revenue, expenses);
- Whether there are items on which the attention of the users of the particular entity's financial report tends to be focused (for example, for the purpose of evaluating financial performance users may tend to focus on profit, revenue or net assets);
- The nature of the entity, where the entity is in its life cycle, and the industry and economic environment in which the entity operates;
- The entity's ownership structure and the way it is financed (for example, if an entity is financed solely by debt rather than equity, users may put more emphasis on assets, and claims on them, than on the entity's earnings); and
- The relative volatility of the benchmark.

Para A6: When, as a starting point, materiality for the financial report as a whole is determined for a particular entity based on a percentage of profit before tax from continuing operations, circumstances that give rise to an exceptional decrease or increase in such profit may lead the auditor to conclude that materiality for the financial report as a whole is more appropriately determined using a **<u>normalised</u>** profit before tax from continuing operations figure based on past results.

ASA 720: The Auditor's Responsibilities Relating to Other Information

- **Other information** – Financial or non-financial information (other than the financial report and the auditor's report thereon) **<u>included in an entity's annual report</u>**.

- **Requirements**: The auditor shall read the other information and
  - consider whether there is a material inconsistency between the other information and the financial report;
  - consider whether there is a material inconsistency between the other information and the auditor's knowledge obtained in the audit, in the context of audit evidence obtained and conclusions reached in the audit.
  - If the auditor identifies that a material inconsistency appears to exist (or becomes aware that the other information appears to be materially misstated), the auditor shall discuss the matter with management.
  - If the auditor concludes that a material misstatement of the other information exists, the auditor shall request management to correct the other information.

Appendix 3.2: The anecdotal evidence about how auditors use non-GAAP earnings metrics as the materiality benchmark

Panel A: Rio Tinto Limited

Results at a glance

		Year to 31 December	2016	2015	Change
KPI	112	Net cash generated from operating activities (US$ millions)	**8,465**	9,383	-10%
KPI	130	Underlying earnings[3] (US$ millions)	**5,100**	4,540	+12%

Based on our professional judgement, we determined materiality for the financial statements and the financial report as a whole as follows:

Overall Group materiality	$275 million (2015: $300 million).
How we determined it	We used an average of underlying earnings before tax (as defined in note 2 to the financial statements) of the current and previous three years (2015: 5% of single year underlying earnings before tax).

Panel B: Myer

NON-IFRS FINANCIAL MEASURES

The Company's results are reported under International Financial Reporting Standards (IFRS) as issued by the International Accounting Standards Board. The Company discloses certain non-IFRS measures in this Directors' Report, which can be reconciled to the Financial Statements as follows:

Income Statement reconciliation

$ millions	EBIT	TAX	NPAT
Statutory reported result	41.0	(18.3)	11.9
Add back: Implementation Costs and Individually Significant Items			
Restructuring and redundancy costs	6.3	(1.9)	4.4
Store exit costs and other asset impairments	48.1	(4.3)	43.8
Support office onerous lease expense and impairment of assets	11.2	(3.4)	7.8
Underlying result	**106.6**	**(27.9)**	**67.9**

Materiality

- For the purpose of our audit we used overall Group materiality of \$4.9 million, which represents approximately 5% of the Group's profit before tax, adjusted for individually material items separately disclosed as restructuring, store exit costs, onerous lease expense and impairment of assets.
- We applied this threshold, together with qualitative considerations, to determine the scope of our audit and the nature, timing and extent of our audit procedures and to evaluate the effect of misstatements on the financial report as a whole.
- We chose Group profit before tax and individually material items separately disclosed because, in our view, it is the metric against which the performance of the Group is most commonly measured by users.
- We adjusted for individually material items as they are unusual or infrequently occurring items impacting profit and loss.
- We selected 5% based on our professional judgement noting that it is also within the range of commonly acceptable profit related materiality thresholds.