THE PREDICTIVE ABILITY AND CLASSIFICATION SHIFTING OF DISCONTINUED OPERATIONS UNDER IFRS – 5

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“Life isn’t about finding yourself. Life is about creating yourself.”

- *George Bernard Shaw*

I dedicate this dissertation to my beloved mother, who has quietly stood by and made sacrifices while showering me with unconditional love and support through all the years I pursued an academic career. It is also dedicated to my honoured father, who is no longer with me. There is no doubt he would have been so proud of his daughter's latest achievement. To them I shall forever be indebted.

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ABSTRACT

Considerable attention has been directed towards the impact of International Financial Reporting Standards (IFRS) by the business community and regulators. IFRS-5 *Non-current Assets Held for Sale and Discontinued Operations* requires the separate reporting of discontinued operations in the statement of comprehensive income. This is based on the (untested) assertion that cash flows from discontinued operations are different from continuing flows. Thus, there is a need to provide empirical evidence to support the assumption.

This thesis examines the usefulness of separate reporting of discontinued operations in two important attributes: predictive ability and classification shifting. Motivated by the concerns that discontinued operations are not useful to predict future profitability and are used to manipulate core earnings, this thesis investigates these two aspects for Australian listed companies that have adopted IFRS since 2005.

Existing literature documents evidence that discontinued operations should be ignored to predict future profitability (Fairfield, Sweeney, & Yohn, 1996) and managers engage in classification shifting using discontinued operations (Barua, Lin, & Sbaraglia, 2010) under the United States' Generally Accepted Accounting Practices (US GAAP). As discontinued operations are defined and measured differently under US GAAP and IFRS, this thesis investigates the usefulness of separate reporting of discontinued operations under IFRS by examining predictive ability and classification shifting of discontinued operations.

The findings show discontinued operations, particularly when splitting it into gains and losses from discontinued operations, are useful to predict a company's future profitability. Furthermore, results show losses from discontinued operations are opportunistically used to manipulate core earnings, to avoid reporting losses and earnings decreases under IFRS, when firms report discontinued operations frequently, and the amount of losses is high.

These results could be used for IASB in deciding whether to report discontinued operations separately in statements of comprehensive income.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ACRONYMS

APE	Absolute Percentage Errors
AFE	Absolute Forecasted Errors
ASC	Accounting Standards Codification
ASU	Accounting Standard Update
CE	Core Earnings
DCO	Discontinued Operations
EPS	Earnings Per Share
FASB	Financial Accounting Standard Board
GAAP	Generally Accepted Accounting Practices
GCU	Cash Generating Unit
IAS	International Accounting Standards
IASB	International Accounting Standard Boards
IASC	International Accounting Standard Committee
IFRIC	International Financial Reporting Interpretations Committee
IFRS	International Financial Reporting Standards
MAPE	Mean Absolute Percentage Error
MoU	Memorandum of Understanding
SEC	Security Exchange Commission
SFAS	Statement of Financial Accounting Standards
US	United States

1. INTRODUCTION

1.1 Background of the Thesis

This thesis investigates one of the current issues in accounting performance reporting, in particular, the usefulness of separate reporting of discontinued operations under IFRS. IFRS-5 *Non-current Assets Held for Sale and Discontinued Operations* requires reporting of discontinued operations separately in the statement of comprehensive income. The line item discontinued operations aggregates income, from a subset of the operations of the firm, that has been identified for disposal or held for sale, and presents this subtotal, after tax, below income from continuing operations. This line item includes sales, expenses, and if the disposal has transpired, the gain or loss from the sale of the sub-set of the business. Accounting standard setters assume that reporting discontinued operations separately from continuing operations provides investors, creditors, and others with information to help assess the effects of disposal transactions on the ongoing operations of an entity. However, there is no evidence discontinued operations should be reported separately in the statement of comprehensive income.

Research indicates that investors focus more on core earnings (i.e. earnings ignoring non-recurring items) compared to total earnings (Bradshaw & Sloan, 2002; Ghani, Laswad, Tooley, & Jusoff, 2009).[1] This is because total earnings include non-recurring items which provide relatively limited information and predictivity about the future performance of a company (Fairfield, Sweeney, & Yohn, 1996; Bradshaw & Sloan, 2002). The academic research to date has tended to focus on special items in Compustat, which contains various non-recurring items like items from discontinued operations and extraordinary items. Extraordinary items are no longer reported in the income statement under IFRS and US-GAAP. Only discontinued items are required to be reported separately under current standards (IASB and FASB). This thesis examines the usefulness of disaggregating total earnings into continuing and discontinued operations in two important ways: predictive ability (useful) and classification shifting (not useful).

[1] Total earnings – sum of continuing and discontinued operations.

1.2 Predictive Ability of Discontinued Operations

1.2.1 Motivation and Hypothesis

Predicting a company's future profitability is important for investors. For non-recurring items, past research has shown mixed results on the usefulness of non-recurring items to predict future profitability.

In general, non-recurring items should be ignored when forecasting future profitability (Cameron & Stephens, 1991; Fairfield, et al., 1996; Bradshaw & Sloan, 2002; Biddle & Choi, 2006). However, some studies show that special items have significant implications for expected future earnings (Burgstahler, Jiambalvo, & Shevlin, 2002; Fairfield, Kitching, & Tang, 2009). Fairfield et al. (2009) find negative special items are associated with future profit margins. Cready, Lopez, and Sisneros (2010) find the frequency of prior reported negative special items has a significant effect on the persistence. That is, as the prior reported negative special items increase, the future earnings implications of current negative special items become more predictable. Most of these studies have examined special items which contain various non-recurring items. This thesis addresses the question of whether reporting discontinued operations separately as required by IFRS – 5, *Non-current Assets Held for Sale and Discontinued Operations* yields useful information for predicting future profitability.

The first objective of this thesis is to provide evidence on the predictive ability of discontinued operations. This thesis further separately examines gains and losses from discontinued operations as they have different implications for future profitability (Fairfield et al., 2009). Additionally, it examines how separating discontinued operations, even splitting into gains and losses, could improve forecasting accuracy to predict a company's future profitability. Finally, this thesis examines whether discontinued operations are informative when averaged over long horizons. Averaging discontinued operations over a longer period has the effect of accumulating and smoothing them over time.

Based on the general perception that non-recurring items are uninformative about one-year-ahead earnings, this thesis addresses the following hypotheses:

Hypothesis (H1): The line item of discontinued operations is not useful in forecasting future earnings under IFRS.

1.2.2 Main Findings

With regard to the first objective, the thesis assesses the predictive ability of discontinued operations. The results show that discontinued operations are useful to predict future profitability. With the splitting of discontinued operations into losses and gains, results show there is a strong association between losses from discontinued operations and one-year-ahead net income. However, gains from discontinued operations are weakly associated with one-year-ahead net income. The findings of the tests do not support the general perception that non-recurring items are uninformative in predicting future profitability. The results reject the hypothesis that discontinued operations are not useful to predict a company's future profitability.

1.3 Classification Shifting of Discontinued Operations

1.3.1 Motivations and Hypotheses

The efficient market and decision usefulness theories support the importance of classifying recurring and non-recurring items.[2] Non-recurring items should be fully disclosed, either in the financial statements proper, or the notes. Otherwise, investors may overestimate the persistence of current reported earnings. Furthermore, prior research on the information content of earnings components demonstrates that the classification scheme prescribed by the accounting profession does increase the predictive content of reported earnings (Fairfield et al., 1996). However, managers opportunistically use classification of earnings components to manipulate core earnings (McVay, 2006). The practice is known as "classification shifting" in accounting literature.

[2] Decision usefulness theory – that is, the ability of financial information to help users make good decisions (Scott, 2009, p72).

Classification shifting is considered one of the earnings management tools. Prior studies demonstrate managers engage in classification shifting using non-recurring items such as extraordinary items (Barnea, Ronen, & Sadan, 1976), special items (McVay, 2006; Fan, Barua, Cready, & Thomas, 2010), other operating income (Noh, Moon, Guiral, & Esteban, 2014), and items from discontinued operations (Barua, et al., 2010) to increase core earnings.

There has been a little discussion about classification shifting of discontinued operations under IFRS.[3] Based on previous literature indicating that non-recurring items are used to manipulate core earnings, I propose the following hypothesis:

> **Hypothesis (H1):** Managers engage in classification shifting using discontinued operations to increase core earnings under IFRS.

Previous studies also provide evidence that managers engage in classification shifting to meet and beat three benchmarks: zero earnings (avoiding a loss), prior year's earnings (avoiding negative earnings) and analysts' forecast (McVay, 2006; Barua et al., 2010; Fan et al., 2010). I hypothesise that managers use classification shifting to meet and beat the following benchmarks under IFRS. Hypotheses are proposed as below:

> **Hypothesis (H2):** Managers use discontinued operations to avoid reporting negative earnings.
>
> **Hypothesis (H3):** Managers use discontinued operations to avoid reporting earnings decreases.

1.3.2 Main Findings

With regard to the second objective, the results reveal discontinued operations are used opportunistically by managers to increase core earnings (H1). The results show unexpected core earnings are strongly associated with losses from discontinued operations in year *t.* There is also an association between losses from discontinued operations and unexpected changes in core earnings in year *t+1*. It is observed that

[3] Noh, Moon, Guiral, & Esteban (2014) investigate whether managers use other income to improve their operating performance in the Korean IFRS adoption period.

classification shifting takes place when firms report discontinued operations frequently and the amount of losses is significantly high. In terms of benchmark-beating tests, there is evidence that managers use classification shifting to avoid losses (H2) and earnings decreases (H3) among firms reporting serial and material discontinued operations.

Overall, the findings support the view that discontinued operations, particularly losses from discontinued operations, are useful to predict future earnings, and in whatever way it is opportunistically used to manage core earnings to avoid reporting losses and earnings decreases under IFRS.

1.4 Contributions of This Thesis

My study contributes to accounting literature in a number of ways. Most importantly, the results provide evidence about discontinued operations to the IASB, in particular, evidence regarding the usefulness of separating discontinued operations for financial performance reporting. Reporting discontinued operations separately in the income statement is based on the (untested) assertion that cash flows from discontinued operations are different from flows from continuing operations. The results of this thesis provide clear evidence that separating discontinued operations under IFRS-5 is useful for predicting future earnings.

Second, this thesis contributes to prediction literature in accounting. Several studies have examined the predictive ability of certain variables such as accruals (Wilson, 1987), inventory (Bernard & Noel, 1991), receivables (Stober, 1993), accounting classification (Fairfield et al., 1996), stock prices (Abarbanell & Bushee, 1997), comprehensive income (Dhaliwal, Subramanyam, & Trezevant, 1998), expenses (Doyle, Lundholm, & Soliman, 2003), income components (Biddle & Choi, 2006), and special items (Fairfield et al., 2009). However, none of these studies examines the predictive ability of discontinued operations.

Third, this thesis contributes to earning management literature, particularly classification shifting under IFRS. There are several classification shifting studies in different countries, such as the US (McVay, 2006; Fan et al., 2010; Barua et al., 2010), Japan, (Shirato & Nagata, 2012), and Korea (Noh et al., 2014). This thesis is undertaken on classification shifting of discontinued operations under IFRS.

Fourth, this study contributes to the literature of non-recurring items. Existing research that is related to non-recurring items including discontinued operations tends to be based on US samples that have adopted a different definition and measurement for discontinued operations. This thesis provides evidence on the two attributes (predictive ability and classification shifting) of discontinued operations from a non-US regime.

Fifth, as FASB released a new amendment with the same definition for IFRS on discontinued operations in August 2014, the result can be considered as evidence in advance for US-GAAP. Or, results could be compared with results from a US sample in the future.

1.5 Framework of This Thesis

The remainder of this thesis is organised as follows. Chapter 2 provides background information on discontinued operations. Chapter 3 provides a literature review on discontinued operations. Chapter 4 provides the literature review for predictive ability, develops hypotheses, describes the research design, and presents the results for the predictive ability of discontinued operations. Chapter 5 reviews the literature, develops hypotheses, describes the research design, and presents the results for classification shifting of discontinued operations. Chapter 6 concludes.

2. BACKGROUND INFORMATION

This chapter discusses the definitions and requirements of reporting assets held for sale and discontinued operations under IFRS-5. The chapter presents IASB and FASB projects that relate to discontinued operations. The chapter also discusses non-recurring items that have been considered separately from continuing operations to review current policy by IASB and FASB.

2.1 IFRS-5 *Non-current Assets Held for Sale and Discontinued Operations*

Discontinuing a business operation is an important event for an entity. This decision is likely to have a significant effect on an entity's performance and net assets. The impact of a discontinued operation and the way in which it is reported is therefore of interest to financial statement users. This is also the subject of a specific IFRS – 5, *Non-current Assets Held for Sale and Discontinued Operations.* IFRS-5 was initially issued on 31 March 2004, and was effective for annual periods beginning on or after 1 January 2005.

IFRS-5.6 states "An entity shall classify a non-current asset (disposal group) as held for sale if its carrying amount will be recovered principally through a sale transaction rather than through continuing use."[4] This definition captures individual assets that the entity seeks to dispose of in a sale transaction such as

- Property plant and equipment
- Intangible assets
- Investment property
- Biological assets, and
- Non-current financial investments such as interests in associates, or other financial instruments.

[4] Disposal group is a group of assets to be disposed of, by sale or otherwise, together as a group in a single transaction. Liabilities directly associated with those assets will be transferred in the transaction. The group includes goodwill acquired in a business combination, if the group is a Cash-Generating Unit (CGU) to which goodwill has been allocated in accordance with the requirements of paragraphs 80 and 87 of IAS 36 *Impairment of Assets*, or if it is an operation within such a cash-generating unit (IFRS-5.A).

2.2 Definition and Requirements for Reporting Discontinued Operations

As defined in the IFRS-5,"discontinued operations are a component of an entity that either has been disposed of, or is classified as held for sale, and (1) represents a separate major line of business or geographical area of operations, (2) is part of a single coordinated plan to dispose of a separate major line of business or geographical area of operations, or (3) is a subsidiary acquired exclusively with a view to resale" (IASB, 2005).

IFRS-5 covers the presentation of discontinued operations. The sum of the post-tax profit or loss of the discontinued operations, and the post-tax gain or loss recognised on the measurement to fair value less cost of sale, or fair value adjustments on the disposal of the assets, is presented as a single amount on the face of the statement of comprehensive income (IFRS-5.33 [a]). IFRS-5 also requires preparers to compute and disclose additional measures of earnings per share (EPS). Reporting discontinued operations separately from continued operations provides investors and other financial information users with information to help assess the effects of disposal transactions on the ongoing operations of a company. Appendix 1 shows the presentation of discontinued operations in the statement of comprehensive income as required by IFRS-5.

IFRS-5 requires disclosures of discontinued operations in the notes. An entity can use different options to present more information in the notes. Appendix 2 is an example of one of the more commonly used options to present discontinued operations. It shows a single line item on the face of the statement of comprehensive income, with further details in the notes. In the example, "Net result from discontinued operations" includes the results from the discontinued operation and the effect of re-measurement and disposal of any assets or disposal groups that constitute the discontinued operations. Also, the analysis includes two tax line items:

- Taxes relating to the operating activities of the discontinued operation until their disposal, and
- Tax effects of re-measurement and disposal of the related assets held for sale or disposal groups.

The result in the highlighted line corresponds to the amount that is presented on the face of the statement of comprehensive income.

In the second example, the net results from discontinued operations, along with analysis of that result, are presented on the face of the statement of comprehensive income. The analysis of discontinued operations is clearly distinguished from the results of continuing operations. The detailed analysis of the results of the discontinued operations is supplemental information on the face of the statement of comprehensive income. This format is commonly used when discontinued operation is or was a very substantial part of total operations.

2.3 The FASB/IASB Project on Discontinued Operations

In 2002, the IASB and FASB began working on a number of projects to accomplish convergence of IFRS and US GAAP. One of these was a joint project on discontinued operations under performance reporting. The objective of this project was to develop a common definition of discontinued operations and require common disclosures about components of an entity that have been (or will be) disposed of. In September 2008, each board issued an exposure draft, with the intention of achieving convergence in reporting discontinued operations. The comment period for the exposure drafts ended on 23 January 2009. After considering respondents' comments on the exposure draft, the FASB and the IASB decided to adopt a common definition of a discontinued operation based on the current definition of IFRS-5. The joint project was discontinued in 2011.

Under both US GAAP and IFRS-5, a discontinued operation is a component of an entity that has been disposed of or held for sale. In addition, both require discontinued operations to be presented separately on the face of the statement of earnings or comprehensive income. However, there are significant differences in how discontinued operations are treated under US GAAP and IFRS. The key difference is the scope of discontinued operations. Under SFAS 144, a component of the entity held for sale falls under discontinued operations presentation if it has operations and cash flows that can be clearly distinguished from the ongoing operations of the entity. The scope of IFRS-5 is much narrower. Separate presentation of discontinued operations is allowed only if the assets to be divested represent a separate major line of business or geographical area of operations. Table 1 summarises the difference between US GAAP and IFRS.

Table 1 Summary of Differences on Discontinued Operations between US GAAP and IFRS

Relevant standards	U S GAAP SFAS 144	IFRS IFRS-5
Unit of account	The unit of account is a component, which may be an operating segment, a reporting unit, a subsidiary or an asset group depending on the facts and circumstances.	The unit of account is a component, which comprises operations and cash flows that can be clearly distinguished, operationally and for financial reporting purposes, from the rest of the entity. A component will have been a cash generating unit when it was held for sale.
Definition	A discontinued operation consists of a component that has been disposed of or classified as held for sale, and that meets both of the following criteria: 1. Operations and cash flows of the components have been or will be eliminated from the ongoing operations of the entity. 2. There will be no significant continuing involvement in the operations of the component after the disposal transaction.	A discontinued operation is a component of an entity that either has been disposed of or classified as held for sale, and that meets any of the following criteria: 1.It represents a separate major line of business or geographical area of operations. 2. It is a part of a single coordinated plan to dispose of a separate major line of business or geographical area of operations. 3. It is a subsidiary acquired exclusively with a plan to resell.

Convergence was supposed to be completed by 2011. As time has passed in the journey toward convergence between IFRS and US GAAP, projects have been delayed over and over again. There are several major factors that seem to prevent IFRS from becoming a financial reporting framework for US domestic issuers: a litigious business environment in the US, FASB's own priorities, politics, and the cost of change (Bogopolsky, 2015). On 10 April 2014, the FASB issued Accounting Standard Update (ASU) No. 2014-08, "Reporting discontinued operations and disclosures of disposals of components of an entity".[5] The IASB itself has been working on a series of issues relating to IFRS-5 since 2013.

[5] Effective in the first quarter of 2015 for public companies with calendar year ends. For most nonpublic entities, it is effective for annual financial statements with years that begin on or after 15 December 2014.

2.4 Non-recurring items

In this section, I discuss non-recurring items that contain special, extraordinary items, and items from discontinued operations. A non-recurring item is generally a gains or a loss found on a company's income statement, and that is not expected to occur regularly. However, according to Kabureck (2017), there is still a challenge in defining non-recurring items.[6] Are non-recurring items based on frequency or size? For example, big companies typically have recurring litigation charges. Most of the time these are small and a normal cost of doing business. But what happens when a company loses a big case? Should non-recurring be a backward-looking or forward-looking test? Or, if all litigation is conceptually the same regardless of size, should it be classified the same way? Kabureck (2017) concludes that the IASB's research project is in its early stages, so it's hard to predict what will eventually transpire.

Special items have been considered as non-recurring in many accounting studies. A special item is a category of Compustat. Compustat defines special items as unusual or non-recurring items presented above net profit before tax. For example, special items include the current year's results of discontinued operations and operations to be discontinued, and flood, fire and other natural disaster losses.

For items of extraordinary and discontinued operations, the IASB and FASB have the same concept and presentation requirements. Extraordinary items are transactions or other events that are both unusual and infrequent in occurrence. The boards decided to eliminate the separate presentation of extraordinary items in the income statement in 2002 and 2015, respectively. In 2002, the IASB decided to eliminate the concept of extraordinary items from IAS 8 *Net Profit or Loss for the Period, Fundamental Errors and Changes in Accounting Policies* and to prohibit the presentation of items of income and expense as "extraordinary items" in the income statement and the notes. IAS 1 *Presentation of Financial Statements*, in paragraph 87, states that an entity shall not treat any items of income or expense as extraordinary in the statement of comprehensive income, the separate income statement (if presented), or in the notes. The main reason is

[6] Gary Kabureck is a member of the International Accounting Standards Board (IASB).

that those items treated as extraordinary result from the normal business risks faced by an entity, and do not warrant presentation in a separate component of the income statement.

On 9 January, 2015, the FASB issued Accounting Standard Update (ASU) 2015-1, *Income Statement-Extraordinary and Unusual Items*, to simplify income statement classification by removing the concept of extraordinary items from US GAAP.[7] The separate, net-of-tax presentation will no longer be allowed. The existing requirement separately to present items that are of an unusual nature, or occur infrequently, on a pre-tax basis within continuing operations, has been retained.

Furthermore, items from discontinued operations items, and other comprehensive income, are reported separately from continuing operations under current standards. Discontinued operations and other comprehensive income are different, however, they are often viewed as similar in nature (Jones & Smith, 2011). Current accounting standards require discontinued operations to be recognised in net income (whether realised or unrealised), while other comprehensive income is deferred until realised. Jones and Smith (2011) document that special items that contain discontinued operations and other comprehensive income differ in terms of their persistence, predictive value and value relevance.

2.5 Chapter Summary

This chapter discusses the definitions and requirements of reporting assets held for sale and discontinued operations under IFRS-5. The chapter presents IASB and FASB projects that relate to discontinued operations. The chapter also discusses non-recurring items that have been considered separately from continuing operations to review current policy by IASB and FASB.

The next chapter surveys the literature regarding discontinued operations.

[7] The standard is effective for both public and private companies for periods beginning after 15 December 2015. Early adoption is permitted.

3. LITERATURE REVIEW ON DISCONTINUED OPERATIONS

There have been few studies on discontinued operations. Barua et al (2010) investigate whether managers use classification shifting to manage earnings when reporting discontinued operations. The main motivation is that the adoption of SFAS 144 has increased the reporting frequency of discontinued operations in the US, and allowed managers more discretion to manage earnings, potentially reducing the quality of reported earnings. They find a positive association between income decreasing discontinued operations and unexpected core earnings in the year a firm reports discontinued operations. This result is consistent with managers shifting operating expenses to discontinued operations. They also find a negative association between discontinued operations and the change in unexpected core earnings in the year after a firm reports discontinued operations, which is consistent with operating expenses returning to core earnings. They extend the benchmark-beating literature and provide evidence that managers engage in classification shifting using discontinued operations to meet or beat analysts' forecasts.

Curtis et al. (2014) examine whether discontinued operations affect the usefulness of disaggregated income in predicting an entity's future continuing income. The study was motivated by the joint FASB/IASB convergence project which sought to define the scope of transactions reported in discontinued operations. They compared the properties of continuing and discontinued operations under two regimes, APB 30 (1973-2002) and SFAS 144 (2002-2014). APB 30 has a similar scope to IFRS-5 in terms of the economic significance of the disposal, but it differs in terms of measurement.[8] SFAS 144 broadened the scope of divestiture transactions to be presented in discontinued operations to components of an entity (rather than segments of a business). Curtis et al. (2014) document that there is a relationship between one-year-ahead continuing income and discontinued operations under SFAS 144. They do not find a positive association between discontinued operations and future operating income under APB 30.

[8] APB 30 required that segments be reported at the lower of carrying amount or net realisable value. SFAS 144 is similar to IFRS-5 which requires an impairment test.

Even though their results support retaining the broader scope (SFAS 144) of discontinued operations, ASU No.2014-08 further narrowed the scope of discontinued operations to only those components of an entity that represent a major line of business or major geographical area of operation (FASB, 2014).

Lord and Saito (2017) investigate the interrelationship between acquisitions and subsequent announcements of discontinued operations, the major reasons for firms to divest operations, and whether announcements of discontinued operations represent the beginning of a process for corporate focus. They find that (1) in the year of an acquisition, companies are less likely to discontinue negative-valued operations, and companies that make large acquisitions are more liable to announce positive-valued discontinued operations in the same year; (2) more widely diversified firms are more likely to discontinue operations; and (3) firms are more likely to divest an operation if they have altered their strategic focus within the previous three-year period.

All these studies were undertaken on US firms that adopted US GAAP. This thesis provides evidence of the predictive ability and classification shifting for discontinued operations under IFRS. Studies on predictive ability and classification shifting are reported in chapters 4 and 5, respectively.

4. PREDICTIVE ABILITY

This chapter provides a literature review of predictive ability for certain earnings components including non-recurring items, and develops hypothesis. It describes the research design and reports results of the predictive ability of discontinued operations. Based on the literature reviewed, hypotheses for usefulness of discontinued operations in forecasting future income is developed. Tests, corresponding to the hypothesis developed along with results, are discussed.

4.1 Literature Review and Hypotheses

4.1.1 Theoretical Framework of Prediction

The prediction of the future profitability of a company is of interest to investors and other financial statement users. Relevant information helps users make predictions about outcomes of present and future events. According to the IASB Conceptual Framework (2010), the objective of financial statements is to provide financial information that is "useful to existing and potential investors, lenders, and other creditors about providing resources to the entity".[9] How can financial statement information be useful in predicting future income? For this, it is necessary to establish some linkage between current firm performance and future prospects. Without such linkage, the decision-oriented objectives of the Framework would not be attainable. Consistent with the information linkage, the Framework states "Information about a reporting entity's past [including current] financial information….is usually helpful in predicting the entity's future returns on its economic resources." This argument enables the Framework to maintain that even though the financial statement report is on current firm financial position and performance, this information can be useful to forward-looking investors.

Beaver, Kennelly, and Voss (1968) define predictive power as the ability to generate operational implications (i.e. predictions) and to have those predictions subsequently verified by empirical evidence.

[9] The IASB Framework was approved by the IASC Board in April 1989. In September 2010, as part of a bigger project to revise the Framework, the IASB revised the objective of the general purpose of financial reporting and the qualitative characteristic of useful information.

Typically, the prediction asserts there is an association between dependent and independent variables such that the outcome of Y is dependent upon the value of X. A considerable amount of literature has been published on different variables that affect a company's future profitability. Financial statement information is regularly employed in prediction models. Such financial statement variables include current net income (Finger, 1994; Dechow, Kothari, & Watts, 1998), core earnings (Fairfield et al., 1996), and non-recurring items (Fairfield et al., 2009). Furthermore, disaggregation of accounting data (Ohlson & Penman, 1992; Fairfield et al., 1996) and firm size (Banz, 1980; Lev, 1983; Collins, Kothari, & Rayburn, 1987; Freeman, 1987; Wild, 1992) have been identified as major contributing variables to predict future profitability.

4.1.2 Net Income

Net income is calculated by taking revenues and subtracting all the costs of doing business, including income from recurring and non-recurring operations. Net income has been considered an important measurement of a company's performance. Finger (1994) tests the ability of net income to predict future net income and future cash flows from operations, one to eight years ahead, using annual data from 1935-87 for 50 firms. He finds that net income is a significant predictor of future earnings, in a sample of 88% of the firms. Also, Dechow, Kothari, & Watts (1998) demonstrate, using a sample of 1,337 firms over 1963-1992, that current net income is a better predictor of future operating cash flow than current operating cash flow.

4.1.3 Core Earnings

Core earnings are recurring earnings, excluding gains or losses from non-recurring items. Core earnings are calculated as the revenue derived from a company's main business, less all operating expenses. Decision-makers tend to give more weight to an information item that they believe is a core activity, compared to a non-recurring item (Ghani et al., 2009). Research reveals that core earnings are more informative than other earnings components for predicting future profitability (Fairfield, et al., 1996; Bradshaw & Sloan, 2002).

4.1.4 Disaggregation

Previous studies disaggregate income statement information in various ways. Ohlson and Penman (1992) evaluate how disaggregated accounting data explain a firm's performance. They focus on regressions, with market returns as the dependent variables, and various components of earnings (gross margins, operating expenses, depreciation expenses, tax expenses, other income/expense items, and extraordinary/unusual line items) as the independent variables. Ohlson and Penman (1992) show that the returns' association to different earnings components differs significantly over short time horizons (five years), but that reactions are similar for components measured over longer horizons (10 years).

Fairfield et al. (1996) examine whether specific income statement classifications yield incremental information for predicting future profitability. They analyse accuracy improvements in out-of-sample forecasts of one-year-ahead return-on-equity (ROE) to examine the predictive content of earnings disaggregation. The results demonstrate that components of earnings increase the predictive content of net income.

4.1.5 Firm Size

Firm size has been associated with a firm's future profit. It has been empirically established that the variability of growth rates in earnings negatively relates to firm size (Banz, 1980; Lev, 1983; Collins et al., 1987; Freeman, 1987; Wild, 1992). The variability of growth rates in large firms is lower than for small firms. Large firms seem to enjoy more stable growth, and their relatively stable growth pattern probably results from diversification into mainly independent operations. Banz (1980) finds that between 1936 and 1975, the common stock of small firms had higher risk-adjusted earnings than the common stock of large firms.

Freeman (1987) investigates the timing and magnitude of the relationship between security returns and accounting earnings for large versus small New York Stock Exchange firms. He finds that security prices of the large firms anticipate accounting earnings earlier than security prices of small firms, and, for a given level of unexpected earnings, the cumulative abnormal returns of small firms exceed those of large firms.

4.1.6 Non-recurring Items and Hypotheses

Researchers have generally assumed non-recurring items to be transitory, that is, to have zero persistence in terms of predicting future profitability (Fairfield et al., 1996; Bradshaw & Sloan, 2002). Investors react more to operating income (core earnings) than to unusual charges (Bradshaw & Sloan, 2002). Some non-recurring items such as write-offs are informationally irrelevant (Ohlson, 1999), and the current practice of classifying non-recurring items decreases the predictive ability of income (Cameron & Stephens, 1991). In contrast, Fairfield et al. (2009) show that negative special items are associated with future profit margins in firms with high profitability. Burgstahler et al. (2002) find that market expectations are sophisticated in that prices reflect differences in implications of special items and non-special items components of earnings for expected future earnings. Non-recurring items receive substantial attention and are assumed to have straightforward implications for expected future earnings. Furthermore, Cready et al. (2010) reveal that as frequency of reporting negative special items increases, the persistence of these items with respect to future earnings significantly increases. That is, the market values "recurring non-recurring" items more like the other components of recurring earnings.

Based on the general perception in existing literature that non-recurring items are uninformative for future earnings, the first hypothesis of this thesis is:

Hypothesis (H1): Discontinued operations are not useful in forecasting future earnings.

4.2 Research Design and Sample

4.2.1 Empirical Models

I follow the Fairfield et al. (2009) model to investigate the predictive ability of discontinued operations. Model (1) is the base model. Model (2) examines the predictive ability of discontinued operations by

disaggregating net income. Model (3) separately investigates the predictive ability of negative and positive discontinued operations. I add firm size as a control variable in the models.[10]

$$NI_t = \sigma_1 + \sigma_1 NI_{t-1} + \sigma_2 \ SIZE_t + \varepsilon_{t-1} \quad (1)$$

$$NI_t = \alpha_0 + \alpha_1 CE_{t-1} + \alpha_2 DCO_{t-1} + \alpha_3 SIZE_t + \varepsilon_t \quad (2)$$

$$NI_t = \eta_0 + \eta_1 CE_{t-1} + \eta_2 NegDCO_{t-1} + \eta_3 PosDCO_{t-1} + \eta_4 SIZE_t + \varepsilon_t \quad (3)$$

where:

NI_t=	Net Income, calculated as (Continuing+Discontinued Income)$_t$ /Total Assets$_{t-1}$
$SIZE_t$=	Natural logarithm of Total Assets$_t$
CE_{t-1}=	Core Earnings$_t$ calculated as (Continuing Income)/Total Assets$_{t-1}$
DCO_{t-1}=	Discontinued Operations/Total Assets$_{t-2}$
$NegDCO_{t-1}$=	Negative DCO_{t-1}/Total Assets$_{t-2,}$ when reported losses from DCO
$PosDCO_{t-1}$=	Positive DCO_{t-1}/Total Assets$_{t-2,}$ when reported gains from DCO

I employ models (1), (2) and (3) for the entire sample and a subsample of firms reporting discontinued operations. The entire sample is tested generally to examine the prediction of one-year-ahead net income for all firms. In the model (1), I run a regression of net income *(NI)* on lagged net income and firm size *(SIZE*). In model (2), I run cross-sectional regressions of firm net income *(NI)* on lagged disaggregated net income, where the components are core earnings *(CE)*, i.e., earnings from continuing operations and discontinued operations *(DCO).* To test whether negative and positive discontinued operations have a differential association with one-year-ahead net income, I separate discontinued operations into negative and positive amounts in model (3).

Fairfield et al. (2009) use sales as a scaler. In my study, all variables are scaled by opening total assets because the mean of sales in my sample is four times lower than total assets, and result in more outliers. I expect that if discontinued operations are not informative about future net income, the coefficients on discontinued operations would be insignificant. To examine the forecast accuracy of separation of

[10] Fairfield et al. (2009) eliminate small firms with either net operating assets or sales of less than $5M. I include all size of firms due to the small sample used. The variable of firm size significantly improves adjusted R^2 (25% to 32%). In untabulated tests I replace SIZE (total assets) with the growth in total assets. The results are qualitatively similar.

discontinued operations, Absolute Percentage Error (APE) and Rank, and Forecast Accuracy tests are employed.

4.2.2 Estimation of APEs and Rank

The Absolute Percentage Errors (APEs) are calculated for Models (1), (2) and (3) at observation level, and are ranked for each model to evaluate forecast accuracy.

APE= $(A_t-F_t)/A_t$

Where:

A_t is the actual value (reported Net Income) and F_t is the forecast value (as calculated Models 1 to 3).

Table 2 shows estimation of APE and rank of APEs across Models 1, 2 and 3. This measures the prediction accuracy of forecasting methods and expresses accuracy as a percentage. Where the percentage error is above 100%, it is reduced to 100%.

Once APEs are calculated, they are ranked for each model at observation level. The model yielding the lowest APE is ranked 1; the highest is ranked 3; and the others are ranked 2. I expect that the more disaggregated model would be ranked lower, which means it has less errors. I use the nonparametric Wilcoxon test on each pair of models (models 1 & 2; 2 & 3; 1&3) to test if they are statistically different. The Mean Absolute Percentage Error (MAPE) is calculated as an average of APEs for tested observations, and they are used to compare average forecast accuracy for three models.

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|,$$

Table 2 Calculation of Absolute Percentage Errors (APE) and Rank

Observations	APE			Ranking		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Observation 1	14%	12%	15%	2	1	3
Observation 2	55%	57%	50%	2	3	1
Observation 3	55%	49%	50%	3	1	2
Observation 4	40%	36%	12%	3	2	1
Observation 5	25%	27%	15%	2	3	1
Observation 6	37%	39%	46%	1	2	3
.						
.						
MAPE	**38%**	**37%**	**31%**	**2.17**	**2**	**1.83**

4.2.3 Forecast Accuracy Test

The Forecast Accuracy Test is an additional test employed by Fairfield et al. (1996), who investigate whether forecast accuracy improves when disaggregating different components of earnings in the prediction models. This test is based on the assumption that if disaggregation improves forecast accuracy, the less disaggregated model has greater errors. I use this methodology to investigate forecast improvements over Models 1, 2 and 3. The test measures the number of observations that forecast accuracy increase or decrease within the sample for models 1, 2 and 3. In other words, how many observations could have forecast accuracy increase, when disagregating net income.

Forecast accuracy is tested only for observations reporting discontinued operations, as a comparable number of observations is available for the DCO sample over different models. Foreacted errors and Absolute Forecasted Errors (AFE) are calculated for Models 1, 2 and 3. Forecasted error is the difference between actual and forecasted net income for each model. AFE is the absolute value of difference between actual and forecasted net income. Then, AFEs are compared between each pair of models (1&2, 2&3, and 1&3) to demonstrate forecast improvement between less and more disaggregated models. I subtract the AFE in the more disaggregated model from the AFE in the less disaggregated model. For example, Forecast Accuracy between Models 1&2 = AFE (Model 1) – AFE (Model 2). A positive difference in less and more disagrregated models indicates that disaggregation improves forecast accuracy.

Fairfield et al. (1996) also assume that if the positive difference is less than 0.005, investors are indifferent to absolute changes in forecast accuracy. Thus, the percentage of observations with 0.005 or more forecast accuracy is presented.

4.2.4 Long Horizon Test

Similar to Fairfield et al. (2009), a Long Horizon test is undertaken as an additional test. This test is important because discontinued operations tend be reported irregularly and might have long run effects on income. It is also necessary for analysts and investors to review financial statements covering longer periods before reaching a conclusion about the profitability of a company. When the earnings window is expanded to two years, the discontinued operations are implicitly smoothed over two years and so on, up to five years. This long horizon test was conducted by Fairfield et al. (2009). I apply models (2) and (3) to examine whether there is an association between future profitabilty in the long run, and discontinued operations.

Table 3 is a diagram of data years included in various horizons. I expect an association between average net income and discontinued operations over windows of increasing length, from one to five years. Averaging discontinued operations over longer periods has the effect of accumulating and smoothing them over time.

Table 3 Data Years Included in One-, Two-, Three-, Four- and Five-year Windows

1-year window		2-year window		3-year window		4-year window		5-year-window	
Dependent Variable	Independent Variable	Dependent Variable	Independent Variable	Dependent Variable	Independent Variable	Dependent Variable	Independent Variable	Dependent Variable	Independent Variable
2016	2015	2015-2016	2013-2014	2014-2016	2011-2013	2013-2016	2009-2012	2012-2016	2007-2011
2015	2014	2014-2015	2012-2013	2013-2015	2010-2012	2012-2015	2008-2011	2011-2015	2006-2010
2014	2013	2013-2014	2011-2012	2012-2014	2009-2011	2011-2014	2007-2010		
2013	2012	2012-2013	2010-2011	2011-2013	2008-2010	2010-2013	2006-2009		
2012	2011	2011-2012	2009-2010	2010-2012	2007-2009				
2011	2010	2010-2011	2008-2009	2009-2011	2006-2008				
2010	2009	2009-2010	2007-2008						
2009	2008	2008-2009	2006-2007						
2008	2007								
2007	2006								

4.2.5 Sample Selection

Australian listed companies that have adopted IFRS since 2005 are selected as a sample.[11] Data are obtained from Thomson Reuters Eikon spanning 2006-2016. The initial data includes 2,135 firms and 18,624 firm-year observations. Table 4 presents the sample composition by year. Firms reporting discontinued operations have significantly increased from 14 firms in 2005 to 263 firms in 2016. Overall, 14.26% of the firms reporting discontinued operations varies by year with a low of 1.46% in year 2005 to a high of 17.40 in 2011 and 2012.

Table 5 demonstrates discontinued operations by year and by industry. The material sector has the highest number of firms reporting discontinued operations, 690 out of the total 2655 (25.99%). Table 6 reports total values of reported discontinued operations by year and by industry. The Consumer Discretionary sector reports a total of 6958M gains, while total value for the Material sector shows 6954M loss from discontinued operations.

Due to the frequency of missing observations, the year 2005 is excluded from the empirical tests. To be included in the sample, firms are required to have no missing observations for the required variables over the period 2006-2016.

I use opening total assets as a scalar. Therefore, observations without opening total assets and continuing income are eliminated. Figure 1 shows the trend in the percentage of firms reporting discontinued operations used in the empirical analysis. The pattern of annual percentages of firms reporting discontinued operations in the sample is similar to that of the entire population. Overall, 11.97% of the total Australian listed firms report discontinued operations in the test period. The percentage of firms reporting discontinued operations varies by year, from a low of 7.95% in 2006 to a high of 13.61% in 2012. In terms of losses of discontinued operations, the trend is similar to that for total discontinued operations, fluctuating between

[11] In 2002, the Financial Reporting Council (FRC) gave a broad strategic direction to the Australian Accounting Standard Board (AASB), requiring the adoption of pronouncements issued by the IASB – the International Financial Reporting Standards (IFRSs). Accordingly, Australian equivalents of IFRSs apply to annual reporting periods beginning on or after 1 January 2005.

4% and 8%. Firms reporting gains for discontinued operation are almost 40% in total. The incidence of firms reporting gains for discontinued operations, however, was roughly stable over the period, ranging between 3% and 6%.

Table 4 Sample Composition by Year (2005-2016)

Fiscal Year	Firm-year observations	Firms Reporting Discontinued Operations	Percentage of Firms Reporting Discontinued Operations
2005	956	14	1.46
2006	1071	96	8.96
2007	1184	153	12.92
2008	1390	194	13.96
2009	1465	223	15.22
2010	1517	249	16.41
2011	1609	280	17.40
2012	1718	299	17.40
2013	1801	292	16.21
2014	1856	291	15.68
2015	1900	301	15.84
2016	2157	263	12.19
Total	**18624**	**2655**	**14.26**

Table 5 Number of Firms Reporting Discontinued Operations by Year and by Industry

Industries	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	**Total**	**%**
Consumer Discretionary	3	16	26	28	29	31	32	34	37	28	28	29	321	12.09
Consumer Staples		5	7	6	6	7	11	10	9	10	9	8	88	3.31
Energy		11	15	24	30	32	37	40	31	33	38	30	321	12.09
Financials	1	6	11	14	12	15	15	19	20	20	24	23	180	6.78
Health Care		11	11	14	14	15	22	20	20	19	17	14	177	6.67
Industrials	3	11	21	27	32	34	38	43	37	40	41	34	361	13.60
Information Technology	1	10	16	24	26	26	24	27	34	37	33	22	280	10.55
Materials	3	20	33	42	57	67	73	77	76	75	85	82	690	25.99
Real Estate	1	2	5	6	8	11	13	15	12	10	10	10	103	3.88
Telecommunication Services		1	4	4	2	3	4	4	3	6	6	5	42	1.58
Utilities	1	2	2	3	4	3	4	3	3	4	4	1	34	1.28
N/A[12]	1	1	2	2	3	5	7	7	10	9	6	5	58	2.18
Total	**14**	**96**	**153**	**194**	**223**	**249**	**280**	**299**	**292**	**291**	**301**	**263**	**2,655**	**100.00**

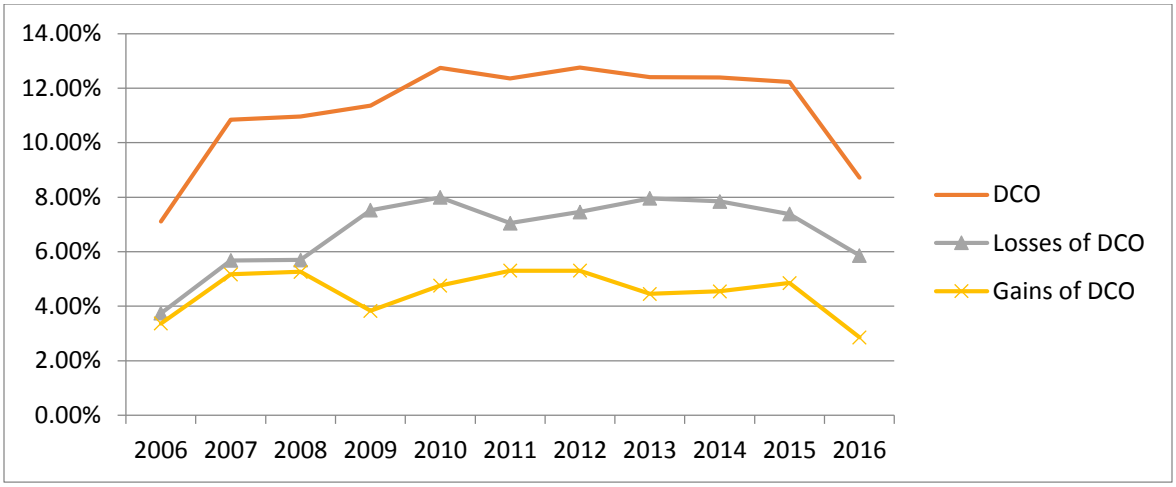
[12] Industries are unavailable.

Table 6 Total Value of Discontinued Operations by Year and by Industry ($'000.000)

Industries	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
Consumer Discretionary	-9	-84	-97	1,588	3,841	-207	231	1,203	664	62	-179	-55	6,958
Consumer Staples		-33	-14	-35	-21	-398	-131	-307	-463	-28	1,181	35	-214
Energy		814	43	-187	105	-4	-45	77	-91	-206	-85	-268	153
Financials			93	197	-30	9	187	6	-344	-276	154	-600	-604
Health Care		262	7	36	-8	-160	-190	-15	-	-2	-16	-39	-125
Industrials		-2	1,485	973	-54	-655	-99	-335	-150	1,657	1,806	-354	4,272
Information Technology	-1	-8	8	26	-61	-87	-101	80	71	-13	-21	-34	-141
Materials	2	25	434	344	-3,368	-970	1,340	-28	-118	-2,435	-153	-2,027	-6,954
Real Estate	3	6	-	14	-1,733	-1,193	273	-31	-192	-51	-130	-102	-3,136
Telecommunication Services			3	38			10			153	-197	18	25
Utilities	46	910	15	60	-63	1,140	-10	-37	-860	-395	26	-285	547
(blank)[13]				-1	-29	-148	-20	22	24	771	5,142	-	5,761
Total	**42**	**1,892**	**1,979**	**3,056**	**-1,425**	**-2,676**	**1,444**	**633**	**-1,460**	**-765**	**7,526**	**-3,713**	**6,533**

[13] Industries are unavailable.

Figure 1 Annual Trend of Percentage of Firms Reporting Discontinued Operations (2006-2016)



4.2.6 Sample Scaling and Criteria

To examine the predictive ability of discontinued operations, one-year-lag data are required. To avoid outliers, past studies eliminate firms with absolute net income greater than one, and core earnings and other variables greater than two (Fairfield et al., 1996; Fairfield et al., 2009). I follow these criteria, but relax the limits from one to two and three respectively. The reason is to avoid eliminating observations and to increase the sample size. Table 7 shows the elimination criteria for firms with absolute net income greater than two, and core earnings and discontinued operations greater than three. Under these criteria, 6.4% of total observations are deleted. The final full sample has 13,562 and the discontinued sample has 1,684 firm-year observations.

Table 7 Sample Selection Criteria for Predictive Ability of Discontinued Operations

Available observations	14491
Absolute Net Income (NI_t) >2	594
Absolute Core Earnings (CE_{t-1})>3	324
Absolute Discontinued Operation (DCO_{t-1})>3	11
Final sample	13562
DCO Sample*	1684

* Observations with discontinued operations.

4.3 Results

4.3.1 Descriptive Statistics

Table 8 provides descriptive statistics for all correlations. Results indicate that samples are statistically different from each other. Panel A presents the descriptive statistics for the full sample. The mean (median) NI for all firms is -0.1830 (-0.0734). The mean (median) core earnings of all firms in the full sample is -0.1867 (-0.0690).

Panels B and C present the descriptive statistics for non-DCO and DCO samples, respectively. Observations with discontinued operations have smaller total assets and a lower loss than those of the non-DCO samples. The mean total assets are 2,158M for firms reporting discontinued operations, which is much less than 2,886M for non-DCO sample. However, the median is higher. The mean (median) of net income is -0.147 (-0.0734) which is lower loss than those for the non-DCO sample.

The Pearson (left side) and Spearman (right side) correlation results are presented in Table 9. Panel A presents for the full, and Panel B for the DCO sample. All variables are significant. The *CE, DCO, NegDCO,* and *SIZE* are positively associated with one-year-ahead *NI*. As predicted, I find that correlation coefficients of *CE* are highest, showing more persistence in predicting one-year ahead net income for all samples.

Table 8 Descriptive Statistics for Predictive Ability

Panel A: Full Sample (N=13562)

Variable	Mean	Std. Deviation	Minimum	Percentiles			Maximum
				25	50	75	
NI_t	-0.183	0.4045	-2.000	-0.3295	-0.0734	0.0516	1.969
CE_{t-1}	-0.1867	0.4608	-2.9928	-0.3166	-0.069	0.0524	2.9781
DCO_{t-1}	-0.0047	0.1058	-2.2075	0.000	0.000	0.000	2.7165
$NegDCO_{t-1}$	-0.0105	0.0782	-2.2075	0.000	0.000	0.000	0.000
$PosDCO_{t-1}$	0.0058	0.0704	0.000	0.000	0.000	0.000	2.7165
$SIZE_t$	7.5685	1.0208	3.8069	6.8556	7.3904	8.1498	11.9461
TA in millions	2795	33458	0	7	24	141	883301

Panel B: Non-DCO Sample (N=11878)

Variable	Mean	Std. Deviation	Minimum	Percentiles			Maximum
				25	50	75	
NI_t	-0.1841	0.3989	-2.0000	-0.3262	-0.0762	0.0501	1.9690
NI_{t-1}	-0.1946	0.4724	-2.9772	-0.3333	-0.0777	0.0542	2.9781
$SIZE_t$	7.5391	1.0085	3.8069	6.8406	7.3593	8.1101	11.9084
TA in millions	2886	34638	0	7	23	129	809870

Panel C: DCO Sample (N=1684)

Variable	Mean	Std. Deviation	Minimum	Percentiles			Maximum
				25	50	75	
NI_t	-0.1474	0.4093	-1.9717	-0.2879	-0.0415	0.057	1.9583
CE_{t-1}	-0.1317	0.3646	-2.9928	-0.2054	-0.0335	0.0414	2.6135
DCO_{t-1}	-0.0377	0.2982	-2.2075	-0.0564	-0.0038	0.0108	2.7165
$NegDCO_{t-1}$	-0.0845	0.2073	-2.2075	-0.0564	-0.0038	0.000	0.000
$PosDCO_{t-1}$	0.0468	0.195	0.000	0.000	0.000	0.0108	2.7165
$SIZE_t$	7.7755	1.0811	5.1673	6.9979	7.6136	8.3944	11.9461
TA in millions	2158	23506	0	10	41	247	883301

Variable definitions:

NI_t= Net Income, calculated as (Continued+Discontinued income)$_t$ /Total Assets$_{t-1}$

$SIZE_{t-1}$= Natural logarithm of opening Total Assets

CE_{t-1}= Core Earnings$_t$, calculated as (Continued Income)/Total Assets$_{t-1}$

DCO_{t-1}= Discontinued Operations/Total Assets$_{t-2}$, when reported DCO, and 0 otherwise

$NegDCO_{t-1}$= Negative DCO_{t-1}/Total Assets$_{t-2,}$ when reported losses DCO, and 0 otherwise

$PosDCO_{t-1}$= Positive DCO_{t-1}/Total Assets$_{t-2,}$ when reported gains from DCO, and 0 otherwise

Table 9 Pearson (left) Spearman (right) Correlation Matrix

Panel A: Full Sample (N-13562)

	NI_t	CE_{t-1}	DCO_{t-1}	$NegDCO_{t-1}$	$PosDCO_{t-0}$	$SIZE_t$
NI_t	1	0.697**	0.059**	0.021*	0.071**	0.566**
		0.000	0.000	0.017	0.000	0.000
CE_{t-1}	0.509**	1	0.042**	0.007	.060**	.607**
	0.000		0.000	0.418	0.000	0.000
DCO_{t-1}	0.032**	0.023**	1	0.793**	0.659**	0.048**
	0.000	0.007		0.000	0.000	.000
$NegDCO_{t-1}$	0.069**	0.047**	0.746**	1	0.065**	-0.011
	0.000	0.000	0.000		0.000	.210
$PosDCO_{t-1}$	-0.028**	-0.017*	0.674**	0.011	1	0.091**
	0.001	0.047	0.000	0.197		.000
$SIZE_t$	0.452**	0.423**	0.043**	0.083**	-0.028**	1
	0.000	0.000	0.000	0.000	0.001	

Panel B: DCO Sample (N-1684)

	NI_t	CE_{t-1}	DCO_{t-1}	$NegDCO_{t-1}$	$PosDCO_{t-0}$	$SIZE_t$
NI_t	1	0.572**	0.216**	0.262**	0.133**	0.450**
		0.000	0.000	0.000	0.000	0.000
CE_{t-1}	0.800**	1	0.207**	0.268**	0.101**	0.552**
	0.000		0.000	0.000	0.000	0.000
DCO_{t-1}	0.679**	0.102**	1	0.967**	0.887**	0.241**
	0.000	0.000		0.000	0.000	0.000
$NegDCO_{t-1}$	0.636**	0.240**	0.759**	1	0.841**	0.320**
	0.000	0.000	0.000		0.000	0.000
$PosDCO_{t-1}$	0.363**	-0.099**	0.722**	0.098**	1	0.092**
	0.000	0.000	0.000	0.000		0.000
$SIZE_t$	0.374**	0.393**	0.140**	0.317**	-0.124**	1
	0.000	0.000	0.000	0.000	0.000	

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

4.3.2 Regression Results

Table 10 reports regression results for models (1), (2), and (3) for the full sample (Panel A), and DCO sample (Panel B). Panel A reports results for the full sample. For model (1), the coefficient on lagged net income is positive and significant (ϵ=0.34, p<0.001). For model (2), the coefficient on discontinued

operations is insignificant, a result consistent with H1. However, for model (3), the coefficients on $NegDCO_{t-1}$ (α=0.141, p<0.001) and $PosDCO_{t-1}$ (η_3=-0.080, p<0.05) are significant.

Panel B reports regression results for observations reporting only discontinued operations. For model (1), the coefficient on lagged net income is positive and significant (α=0.050, p<0.1), a result consistent with the full sample (ε=0.191, p<0.001). For model (2), the coefficient on discontinued operations is weakly significant (α=0.050, p<0.1), a result inconsistent with H1 that discontinued operations are not useful to predict future profitability. For model (3), the coefficients on $NegDCO_{t-1}$ are both positive and significant (η_3=0.220, p<0.001), and on $PosDCO_{t-1}$ it is significant (η_3=-0.123, p<0.01). As predicted, core earnings (*CE*) and firm size *(SIZE)* are positive and significant for one-year-ahead net income. The coefficients on *CE* are 0.340 for a full sample and 0.302 for a DCO sample, confirming the relatively high persistence of core earnings.

Overall, the results show that discontinued operations, in particular, losses and gains from discontinued operations, are significant in Table 10. Thus, Hypothesis H1: the line item of discontinued operations is not useful in forecasting future earnings under IFRS, is rejected.

Table 10 Regression of Net Income (NI) on Discontinued Operations (DCO)

Panel A: Full Sample (N=13562)

Independent	Model 1		Model 2		Model 3	
Variables	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.983	-40.849***	-0.981	-40.756***	-0.973	-40.324***
NI_{t-1}	0.34	49.833***				
CE_{t-1}			0.34	49.826***	0.34	49.800***
DCO_{t-1}			0.042	1.542		
$NegDCO_{t-1}$					0.141	3.863***
$PosDCO_{t-1}$					-0.08	-1.981**
$SIZE_t$	0.114	37.013***	0.114	36.934***	0.113	36.615***
F statistic	3216.233***		2200 .488***		1656.289***	
Adjusted R^2	32.17%		32.73%		32.81%	

Panel B: DCO sample (N=1684)

Independent	Model 1		Model 2		Model 3	
Variables	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.985	-13.783***	-0.904	-12.559***	-0.792	-10.570***
NI_{t-1}	0.191	9.759***				
CE_{t-1}			0.302	11.400***	0.284	10.656***
DCO_{t-1}			0.05	1.651*		
$NegDCO_{t-1}$					0.22	4.798***
$PosDCO_{t-1}$					-0.123	-2.659**
$SIZE_t$	0.112	12.501***	0.103	11.421***	0.091	9.838***
F statistic	199.371***		148.380***		118.815***	
Adjusted R^2	19.08%		20.81%		21.88%	

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively.

4.3.3 Estimation of APEs and Rank

Table 11 reports the MAPE results for full and DCO samples. APE is calculated as the difference between actual and forecasted net income divided by actual net income for each observation, where forecasted net income is estimated using Models (1), (2) and (3). MAPE is estimated as mean of total APEs for each model. Results show that MAPE is lower in the more disaggregated models, confirming that separating discontinued operation is useful in forecasting future profitability. For the ranking, less disaggregated models are ranked higher, consistent with MAPE results. The Wilcoxon signed rank test is used to examine ranks that are statistically different for each pair of models (1 & 2; 2 & 3).

Table 11 Mean Absolute Percentage Error and Rank

Models from less to more disaggregated		Full sample	Rank	DCO Sample	Rank
1	$NI_t = \alpha_1 + \alpha_1 NI_{t-1} + \alpha_2 SIZE_{t-1} + \varepsilon_{t-1}$	70.53%	2.30***	75.57%	2.28***
2	$NI_t = \alpha_1 + \alpha_1 CE_{t-1} + \alpha_2 DCO_{t-1} + \alpha_3 SIZE_{t-1} + \varepsilon_{t-1}$	70.32%	2.02***	74.43%	1.97***
3	$NI_t = \alpha_1 + \alpha_1 CE_{t-1} + \alpha_2 NegDCO_{t-1} + \alpha_3 PosDCO_{t-1} + \alpha_4 SIZE_{t-1} + \varepsilon_{t-1}$	70.25%	1.79***	74.02%	1.73***

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, using the Wilcoxon signed rank test.

NI_t= Net Income, calculated as (Continuing+Discontinued income)$_t$ /Total Assets$_{t-1}$

$SIZE_t$= Natural logarithm of Total Assets$_t$

CE_{t-1}= Core Earnings$_t$, calculated as (Continuing Income)/Total Assets$_{t-1}$

DCO_{t-1}= Discontinued Operations/Total Assets$_{t-2}$, when reported DCO, and 0 otherwise

$NegDCO_{t-1}$= Negative DCO_{t-1}/Total Assets$_{t-2,}$ when reported losses from DCO, and 0 otherwise

$PosDCO_{t-1}$= Positive DCO_{t-1}/Total Assets$_{t-2,}$ when reported gains from DCO, and 0 otherwise

4.3.4 Forecast Accuracy Test Results

Table 12 reports descriptive statistics on Forecast Errors and Absolute Forecast Errors for Full (Panel A) and DCO (Panel B) samples. For the full sample, it is observed that there are not large differences in means and medians for Models (1), (2), and (3). However, Panel B indicates that means of AFEs in less aggregated

models are greater than those of more aggregated models (0.238 for Model 1, 0.232 for Model 2 and 0.229 for Model 3), supporting the idea that disaggregating net income improves forecast accuracy.

Table 12 Descriptive Statistics on Forecast Errors and Absolute Forecast Errors

Panel A: Full Sample N=13562							
		Forecast Errors[a]			Absolute Forecast Errors[b]		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Mean		0.000	0.000	0.000	0.219	0.219	0.219
Std. Deviation		0.332	0.332	0.331	0.249	0.249	0.249
Minimum		-1.808	-1.809	-1.810	0.000	0.000	0.000
Percentiles	25	-0.114	-0.115	-0.114	0.068	0.068	0.068
	Median	0.042	0.042	0.042	0.142	0.142	0.141
	75	0.154	0.154	0.154	0.267	0.267	0.266
Maximum		2.873	2.879	2.890	2.873	2.879	2.890
Panel B: DCO Sample N=1684							
Mean		0.000	0.000	0.000	0.238	0.232	0.229
Std. Deviation		0.368	0.364	0.361	0.280	0.280	0.280
Minimum		-1.823	-1.630	-1.637	0.000	0.000	0.000
Percentiles	25	-0.139	-0.129	-0.126	0.075	0.071	0.068
	Median	0.030	0.031	0.029	0.151	0.142	0.138
	75	0.158	0.148	0.141	0.283	0.277	0.275
Maximum		2.685	2.803	2.751	2.685	2.803	2.751

[a] Forecast Error = Actual Net Income-Forecasted Net Income

[b] Absolute Forecast Error = absolute value of (Actual Net Income-Forecasted Net Income)

Model l - $NI_t = \sigma_1 + \sigma_1 NI_{t-1} + \sigma_2 SIZE_{t-1} + \varepsilon_{t-1}$

Model 2 - $NI_t = \alpha_0 + \alpha_1 CE_{t-1} + \alpha_2 DCO_{t-1} + \alpha_3 SIZE_t + \varepsilon_t$

Model 3 - $NI_t = \eta_0 + \eta_1 CE_{t-1} + \eta_2 PosDCO_{t-1} + \eta_3 NegDCO_{t-1} + \eta_4 SIZE_t + \varepsilon_t$

Table 13 reports the forecast improvement from disaggregating net income for different models 1&2 (Panel A), 2&3 (Panel B), and 1&3 (Panel C). Positive difference would indicate the improvement of forecast accuracy. Results show that the proportion of firms with increased forecast accuracy is greater than the proportion with decreased accuracy, for all pairs of Models. The percentage of increases in forecast accuracy between less and more disaggregated models are 63.78% (models 1&2), 61.64% (models 2&3), and 64.85% (models 1&3) respectively, indicating the proportion of firms with increased forecast accuracy is significantly larger than the proportion with decreased accuracy.

Table 13 Forecast Improvement from Disaggregating Net Income

		DCO sample	Accuracy Increase[a]	Accuracy Decrease[b]	Accuracy Increase>0.005
Panel A: Forecast Improvement from Using Model 2 over Model 1					
N		1684	1074	610	882
Proportion of Increase or Decrease		100.00%	63.78%	36.22%	82.12%
Mean		0.006	0.028	-0.033	0.034
Std. Deviation		0.052	0.042	0.046	0.044
Minimum		-0.310	0.000	-0.310	0.005
	25	-0.008	0.007	-0.041	0.010
Percentiles	Median	0.006***	0.014***	-0.017***	0.019***
	75	0.020	0.031	-0.005	0.036
Maximum		0.411	0.411	0.000	0.411
Panel B: Forecast Improvement from Using Model 3 over Model 2					
N		1684	1038	646	871
Proportion of Increase or Decrease		100.00%	61.64%	38.36%	83.91%
Mean		0.003	0.022	-0.026	0.026
Std. Deviation		0.040	0.031	0.035	0.032
Minimum		-0.321	0.000	-0.321	0.005
	25	-0.010	0.008	-0.032	0.011
Percentiles	Median	0.006***	0.015***	-0.018***	0.017***
	75	0.018	0.026	-0.007	0.028
Maximum		0.425	0.425	0.000	0.425
Panel C: Forecast Improvement from Using Model 3 over Model 1					
N		1684	1092	592	986
Proportion of Increase or Decrease		100.00%	64.85%	35.15%	90.29%
Mean		0.009	0.032	-0.032	0.035
Std. Deviation		0.058	0.053	0.045	0.054
Minimum		-0.575	0.000	-0.575	0.005
	25	-0.011	0.012	-0.035	0.014
Percentiles	Median	0.010***	0.022***	-0.021***	0.024***
	75	0.027	0.035	-0.010	0.036
Maximum		0.809	0.809	0.000	0.809

Significance levels AFEs are calculated using Wilcoxon signed rank tests on improvements.

[a] Accuracy Increase Positive difference in AFEs between more and less disaggregated models.

[b] Accuracy Decrease Negative difference in AFEs between more and less disaggregated models.

Fairfield et al. (1996) assume that investors are indifferent to absolute changes in forecast accuracy less than a threshold of 0.005. The last column reports the forecast accuracy increases over 0.005. It is observed that higher percentages of observations (82.12% in models 1&2, 83.91% in models 2&3, and 90.29% in models 1&3) forecast accuracy improvement of 0.005 and more, demonstrating that separating discontinued operations, and even splitting discontinued operations into losses and gains, improves forecast accuracy. This finding supports classification of earnings under IFRS into income from continued and discontinued operations as clearly increasing the predictive content of reported earnings.

4.3.5 Long Horizon Test Results

Table 14 reports regression results using earnings windows of increasing size for a full sample (Panel A) and a DCO sample (Panel B). In the first rows of Panels A and B, regression results are the same as results from the primary analysis in Table 10. In the next four rows of each panel, I report regression results over earnings windows of increasing size. In each row, the earnings windows for the dependent and independent variables are expanded by one year, so that the dependent variable in the two-year window is net income (NI) for years *t* and *t+1,* and independent variables are the average core earnings (CE) and average discontinued operations (DCO), scaled by opening total assets, for years *t-1* and *t-2.*

For models (2) and (3) in Panel A, adjusted R^2 are likely to increase monotonically as the window size increases. For model (2), the coefficients on discontinued operations are significant except for the one- and five-year windows. Even though the coefficient on discontinued operations is positively associated with one-year-ahead net income in the first window, the coefficients in the second- to the fifth-year window are negatively associated with future performance. For model (3), coefficients on negative discontinued operations are significant with net income for the majority of windows except the fifth window. However, coefficients from the second to the fifth year are negatively associated with future profitability.

Panel B provides regression results for the DCO sample. For model (2), the coefficients on core earnings increase as the window size increases, from 0.302 to 0.401, consistent with the results of Fairfield et al

(2009). The adjusted R^2 are relatively lower than the full sample. For model (2), results from discontinued operations are similar to the results from the full sample. For model (3), all negative discontinued operations variables are significant at the 1% and 5% levels, except for the five-year window. However, coefficients on positive discontinued operations are not significant over longer windows.

Overall, the results of models (2) and (3) with the long horizon test support the view that negative discontinued operations are associated with future income, but there is no association between positive discontinued operations and future income in longer windows.

There are a couple of exceptions. The coefficients on discontinued/negative discontinued operations are negatively associated with future performance in sequential windows. Next, significance level tends to increase as windows size increases, demonstrating that averaging discontinued operations does improve their explanatory power for future profitability, consistent with results from Fairfield et al. (2009). An implication of this outcome is the possibility that frequency of reporting non-recurring items increases predictive ability of future profitability (Cready et al., 2010).

Table 14 Regression Results in Long Horizon

Panel A: Full Sample

	Model 2					Model 3					
Windows	Intercept	CE	DCO	SIZE	R^2	Intercept	CE	NegDCO	PosDCO	SIZE	R^2
1 (N=13562)	-0.981	0.34	0.042	0.114	32.70%	-0.973	0.34	0.141	-0.08	0.113	32.80%
	-40.756***	49.826***	1.542	36.934***		-40.324***	49.800***	3.863***	-1.981**	36.615***	
2 (N=10419)	-1.098	0.333	-0.071	0.128	38.40%	-1.104	0.333	-0.156	-0.001	0.128	38.50%
	-44.945***	43.522***	-2.388**	41.149***		-44.987***	43.566***	-3.485***	-0.024	41.230***	
3 (N=7159)	-1.028	0.338	-0.124	0.121	50.60%	-1.033	0.338	-0.192	-0.057	0.121	50.60%
	-45.703***	55.552***	-3.807***	42.122***		-45.636***	55.559***	-4.113***	-1.228	42.134***	
4 (N=4009)	-1.023	0.318	-0.091	0.12	48.70%	-1.025	0.318	-0.112	-0.054	0.12	48.70%
	-37.363***	39.600***	-1.765*	34.501***		-37.169***	39.597***	-1.715*	-0.625	34.405***	
5 (N=1945)	-0.939	0.358	-0.067	0.108	43.20%	-0.94	0.358	-0.08	-0.038	0.109	43.20%
	-21.508***	20.076***	-0.729	19.912***		-21.399***	20.066***	-0.714	-0.223	19.856***	

	Model 2					Model 3					
Panel B: DCO Sample											
Windows	Intercept	CE	DCO	SIZE	R^2	Intercept	CE	NegDCO	PosDCO	SIZE	R^2
1 (N=1684)	-0.904	0.302	0.05	0.103	20.80%	-0.792	0.284	0.22	-0.123	0.091	21.90%
	-12.559***	11.400***	1.651*	11.421***		-10.570***	10.656***	4.798***	-2.659**	9.838***	
2 (N=1783)	-1.012	0.273	-0.052	0.116	27.70%	-1.03	0.277	-0.1	-0.018	0.118	27.70%
	-17.511***	11.894***	-1.668*	16.017***		-17.218***	11.938***	-1.911**	-0.409	15.895***	
3 (N=1544)	-1	0.313	-0.119	0.116	44.00%	-1.026	0.315	-0.197	-0.051	0.119	44.10%
	-21.308***	20.794***	-3.586***	19.554***		-21.074***	20.899***	-3.819***	-1.068	19.532***	
4 (N=1113)	-1.025	0.333	-0.113	0.118	46.20%	-1.047	0.336	-0.197	0.006	0.121	46.30%
	-18.732***	18.080***	-2.064**	17.219***		-18.551***	18.155***	-2.596**	0.068	17.211***	
5 (N=551)	-0.915	0.401	-0.082	0.106	44.40%	-0.927	0.403	-0.128	0.003	0.107	44.40%
	-11.143***	10.991***	-0.872	10.496***		-10.919***	10.991***	-1.029	0.017	10.387***	

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively.

NI_t= Net Income, calculated as (Continuing+Discontinued income)$_t$ /Total Assets$_{t-1}$

$SIZE_t$= Natural logarithm of Total Assets$_t$

CE_{t-1}= Core Earnings$_t$, calculated as (Continuing Income)/Total Assets$_{t-1}$

DCO_{t-1}= Discontinued Operations/Total Assets$_{t-2}$, when reported DCO, and 0 otherwise

$NegDCO_{t-1}$= Negative DCO_{t-1}/Total Assets$_{t-2,}$ when reported losses from DCO, and 0 otherwise

$PosDCO_{t-1}$= Positive DCO_{t-1}/Total Assets$_{t-2,}$ when reported gains from DCO, and 0 otherwise

4.4 Chapter Summary

This chapter reviews literature for predictive ability, develops the hypothesis and describes research design, and presents results for predictive ability of discontinued operations. It provides an overview of existing literature relating to the predictive ability of certain financial variables. This overview discusses how financial variables such as net income, core earnings, disaggregation of accounting data and firm size have important roles in predicting a company's future profitability. Existing literature generally supports and documents that non-recurring items are uninformative for predicting a company's future performance (Fairfield et al., 1996; Bradshaw & Sloan, 2002; Burgstahler et al. 2002; Biddle & Choi, 2006). However, other studies have discovered that negative non-recurring items contain information to forecast future profit (Fairfield et al., 2009; Cready et al., 2010).

With respect to the research design, the Fairfield (2009) prediction model is applied as the main test. Furthermore, forecast accuracy and prediction error are also undertaken. The long horizon test is used to examine the association between future profitability and discontinued operations in a longer period of more than one year.

The result shows discontinued operations are statistically significant for the full and DCO samples. These findings are inconsistent with past research (Fairfield et al., 1996) that found discontinued operations should be excluded from forecasting one-year-ahead net income. Losses from discontinued operations are positively and significantly associated with one-year-ahead net income, and these results reject H1: discontinued operations are not useful to predict future net income. Results from MAPE and forecast

accuracy tests show that separating discontinued operations improves the forecast accuracy of predicting future profitability. In the long run, only losses from discontinued operations are useful to forecast future performance. An implication of this is the possibility that discontinuing loss-making operations for the preceding year positively affects a company's future performance.

The next chapter examines classification shifting of discontinued operations.

5. CLASSIFICATION SHIFTING OF DISCONTINUED OPERATIONS

This chapter provides a literature review of classification shifting. It describes the research designs and reports the results of the classification shifting of discontinued operations. Based on the literature, hypotheses for classification shifting using a discontinued operation are developed. Tests corresponding to the three hypotheses developed, along with results, are discussed.

5.1 Literature Review and Hypothesis Development

5.1.1 Classification Shifting is a Tool of Earnings Management

The financial reporting process provides opportunities for earnings management. IFRS do not completely constrain a manager's choice of accounting policies and procedures. Such choices are much more complex and challenging than simply selecting those policies and procedures that best inform investors. Rather, the manager's accounting policy choices are often motivated by strategic considerations such as meeting earnings expectations, and contracts that contain financial accounting variables.

Healy & Wahlen (1999) define earnings management as follows:

> Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting practices (Healy & Wahlen 1999, p.368).

Previous research has shown that firms manage earnings. For example, Burgstahler and Dichev (1997) suggest that an observed asymmetry in the distribution of earnings is consistent with firms managing earnings to avoid earnings benchmarks. They examine US data from Compustat 1976-1994 and find there are more observations with small profits than expected, and fewer observations with small losses than expected. Similar earnings distributions have been observed in other countries including the UK (Gore,

Pope, & Singh, 2002), Australia (Holland & Ramsay 2003), Japan (Thomas, Herrmann, & Inoue, 2004), Germany (Glaum, Lichtblau, & Lindemann, 2004), and New Zealand (Bennett & Bradbury, 2007).

Prior literature has also shown the motives of earnings management differ between countries due to the institutional environment. The US research focuses on motives for earnings management related to capital markets, management compensation, lending contracts, and industry. (Healy & Wahlen, 1999; Bartov et al., 2002; Glaum et al., 2004). By contast, European countries, Australia, and New Zealand consider tax and dividend payments as additional incentives for earnings management (Glaum et al., 2004; Bennett & Bradbury, 2007).

Literature has focused on three general earnings management tools: accruals management (DeFond & Jaimbalo, 1994; Burgstahler & Dichev, 1997; Rayne & Robb, 2000), the manipulation of real activities (Bartov, 1993; Dechow, Sloan, & Sweeney, 1995; Roychowdhury, 2006), and classification shifting (McVay, 2006; Barua et al.,2010; Fan et al., 2010).

In order to assist financial information users to value a company's performance, items from discontinued operations are separately disclosed in the income statement (IFRS-5). However, the separation of net income into recurring and non-recurring components gives managers the opportunity to misclassify income and expense items (McVay, 2006; Barua et al., 2010). This is known as "classification shifting".

In addition, the issue of income classification shifting is of high importance to regulators: "The appropriate classification of amounts within the income statement is as important as the appropriate measurement or recognition of such amount" (SEC, 2000b). The SEC further stresses that they are concerned about classification shifting because they have noted a number of improper classifications of line items in financial statements, especially the income statement. For example, on 12 November 2009, the SEC charged SafeNet, Inc., and Symbol Technologies, Inc. with improper classification of ordinary expenses to a restructuring charge (SEC, 2009).

5.1.2 Classification Shifting and Hypothesis Development

Classification shifting has been recognised as a form of earnings management. As defined by McVay (2006), classification shifting is misclassifying core expenses into non-recurring items to boost core earnings. It does not change the reported final net income, and focuses on allocation of expenses between core earnings and non-recurring items. Table 15 presents an illustration of classification shifting. As can be seen, managers could report operating expenses as losses from discontinued operations, with a resulting increase in core earnings.

Table 15 Illustration of Classification Shifting

	Before Classification Shifting	After Classification Shifting
Income from operation	$100	$100
Operating expenses	($85)	($80)
Core earnings	**$15**	**$20**
Loss from discontinued operations	($5)	($10)
Net Income	**$10**	**$10**

Compared with accruals and real earnings management, classification shifting has several advantages (McVay, 2006). It is less costly to implement, does not involve accruals that need to be reversed, and there are no adverse economic consequences that affect real earnings management activities. Thus, income classification shifting can be a viable tool for managers to meet market expectations (McVay, 2006; Barua et al., 2010; Fan et al., 2010).

Barnea et al. (1976) find extraordinary items are used to smooth operating income. Subsequent literature has documented that managers opportunistically shift core expenses to non-recurring items. It has been demonstrated that managers use different non-recurring items such as special items (McVay, 2006; Fan et al., 2010), other operating income (Noh et al., 2014), and items from discontinued operations (Barua, et al., 2010) to manage core earnings.

A large and growing body of literature has investigated classification shifting for the last two decades. McVay (2006) investigates whether managers engage in classification shifting by reporting core expenses

in negative special items. She examines 76,901 US firm-year observations from Compustat between 1989 and 2003, and develops an expected core earnings model to estimate unexpected core earnings and unexpected changes in core earnings. She finds special items are positively associated with unexpected core earnings, and negatively associated with the unexpected change in core earnings in the following year. These results are consistent with the hypothesis that managers shift operating expenses to special items.

Fan et al. (2010) extend McVay's (2006) core earnings expectation models by controlling for performance using returns and lagged returns rather than current accruals.[14] Fan et al.'s (2010) results show that classification shifting is more likely in the fourth quarter than in interim quarters. Also, they provide evidence of classification shifting when the ability of managers to manipulate accruals appears to be constrained in meeting a range of earnings benchmarks. Barua et al. (2010) examine classification shifting between core expenses and discontinued operations in the US context, and provide evidence that firms shift core expenses to income-decreasing discontinued operations to increase core earnings.

Classification shifting has also been extended by several more recent studies (Abernathy, Rapley, & Beyer, 2014; Lail, Thomas, & Winterbotham, 2014; Alfonso, Cheng, & Pan, 2015). Abernathy et al. (2014) find that managers are more likely to use classification shifting when real earnings management is constrained by poor financial conditions, high levels of institutional ownership, and low industry market share. Lail et al. (2014) demonstrate that expenses are also shifted from core segments to a corporate's other segment, while Alfonso et al. (2015) reveal that the market's expectation of core earnings' persistence is higher than the actual reported earnings' persistence of firms that have shifted their core earnings.

Several studies have used the McVay (2006) models to investigate classification shifting, not only in the US (Barau et al. 2010; Fan et al. 2010) but in Japan (Shirato & Nagata, 2012), Korea (Noh & Moon, 2014), and other East Asian countries (Haw, Ho, & Li, 2011). Shirota and Nagata (2012) investigate the classification shifting under Japanese GAAP that allow managers wider discretion over classification

[14] Fan et al. (2010) assert that the association between negative special items, unexpected core earnings, and unexpected changes in core earnings may be biased of because non-cash special items that are included in accruals. However, Barua et al. (2010) document that there is no potential bias in using the McVay (2006) model for discontinued operations because these results are reported separately from the results of continuing operations.

shifting of other revenues and non-operating expenses. Consistent with the US, they find a strong tendency to shift expenses (gains) downward (upward) to increase core earnings. Noh and Moon (2014) provide evidence that managers opportunistically use other income in a general shifting practice in the Korean IFRS adoption period. Haw et al. (2011) also provide evidence of the pervasiveness of classification shifting in eight East Asian countries characterised by the prevalence of family-controlled businesses, close ties between controlling families and top executives, relationship-based business networks, and high levels of government and political influence.[15] No research has been conducted into classification shifting of discontinued operations under IFRS.

Based on the evidence in current literature that managers opportunistically use non-recurring items to increase core earnings, I expect that discontinued operations can be used to manipulate core earnings under IFRS. This leads to the following hypothesis:

> **Hypothesis (H1)**: Managers engage in classification shifting use discontinued operations to increase core earnings.

5.1.3 Classification Shifting to Meet or Beat Earnings Benchmarks

A frequently examined motivation for earnings management reflects managers' incentives to meet or beat earnings benchmarks, including zero earnings, prior year's earnings and analysts' forecasts (McVay, 2006, Barua et al., 2010; Fan et al., 2010). Managers try to meet or beat benchmarks because shareholders use these benchmarks to evaluate firm performance (Burgstahler et al., 1997; Degeorge et al., 1999). Other reasons why managers wish to meet earnings benchmarks include capital market motivations to improve share price performance. Meeting the benchmarks may improve stock price of a firm, while missing the benchmarks may negatively affect the stock price and increase the cost of capital (Graham, Harvey, & Rajgopal, 2005).

[15] South Korea, Thailand, Taiwan, Singapore, Malaysia, Indonesia and the Philippines.

A company's profit is used to help monitor and regulate contracts between a company and its stakeholders. By avoiding losses and/or earnings decreases, the company is perceived to be more stable and reliable therefore can get more favorable terms from suppliers and lenders and attract better employees (Holland & Ramsay, 2003). A further issue is compensation contracts (Healy & Wahlen, 1999; Holland & Ramsay, 2003; Glaum et al., 2004). Managers' compensation is often based on achieving earnings benchmarks, and reputations and job security also hinge on such achievements (Graham et al., 2005). Furthermore, research shows that meeting or beating benchmarks results in a higher return for firms than occurs when firms fail to meet these expectations (Bartov, Givoly, & Hayn, 2002). There is also a higher probability of bond rating upgrades and a smaller initial bond yield spread (Jiang, 2008).

McVay's (2006) research shows that classification shifting tends to occur more often when it allows managers to meet analysts' forecasts. Barua et al.'s (2010) results suggest that companies go further, reporting negative discontinued operations use classification shifting to increase core earnings change to meet or beat the analysts' forecast benchmark. Fan et al. (2010) find classification shifting enables meeting three benchmarks: analysts' forecast, one-year-ago same-quarter earnings, and zero earnings. They find greater evidence of classification shifting for samples that meet or narrowly beat these three benchmarks.

Based on the existing literature, I expect that managers use discontinued operations to meet or beat the following benchmarks: zero earnings (avoiding a loss), and prior year's earnings (avoiding negative earnings).[16] I propose the following hypotheses:

Hypothesis (H2): Managers use discontinued operations to avoid reporting losses.

Hypothesis (H3): Managers use discontinued operations to avoid reporting earnings decreases.

[16] Meeting and beating analysts' expectations are not examined in this thesis, because of the lack of data to investigate this benchmark in the Australian sample.

5.2 Research Design

5.2.1 Empirical Models for Classification Shifting

I adopt McVay's (2006) approach. First, I estimate expected core earnings in the year *t* and expected change in core earnings in the year *t+1* using the following models:

$$CE_t = \alpha_0+\alpha_1 CE_{t-1}+\alpha_2 ACC_t+\alpha_3 ACC_{t-1}+\alpha_4 \Delta TA_t + Neg\Delta TA_t + e_t \quad (1)$$

$$\Delta CE_t = \beta_0+\beta_1 \Delta CE_t + \beta_2 CE_{t-1}+\beta_3 ACC_t + \beta_4 ACC_{t-1} + \beta_5 \Delta TA_t + Neg\Delta TA_t + \nu_t \quad (2)$$

where:

CE_t =	Core Earnings, calculated as net profit before discontinued operations/TA_{t-1}
ACC_t =	Operating Accruals, calculated as (net income before discontinued operations-cash from operations$_t$)/TA_{t-1}
ΔTA_t =	Change in Total Assets, calculated as (TA_t-TA_{t-1})/TA_{t-1}
$Neg\Delta TA_t$ =	Percent change in TA, calculated as (ΔTA_t) if ΔTA_t, is less than 0 and 0 otherwise
ΔCE_t =	Change in Core Earnings, calculated as CE_t-CE_{t-1}

McVay (2006) includes Asset Turnover Ratio (ATO) in the model of expected earnings. I do not include ATO in the model as it is related to profit margin. There are three reasons for this decision. First, I use opening total assets as a scalar. However, the results are not sensitive to this choice. Second, it avoids more data elimination. That is, 8.3% of firms with discontinued operations report no sales, but they do report total assets. The average total assets is around four times larger than average sales. Thus, scaling variables by total assets reduces outliers. Third, ATO is weakly significant in McVay (2006).

Accruals are included in the model because Sloan (1996) finds that current and lagged accruals are an explanatory variable for future performance. I include changes in total assets and negative changes in total assets as explantory variables.[17]

To provide evidence of classification shifting, I regress unexpected core earnings and unexpected change in core earnings on losses and gains from discontinued operations as below:

[17] McVay (2006) uses sales as a scalar and includes sales growth ($\Delta SALES_t$) as an explanatory variable. She also includes NegΔSales as a control variable due to the difference between sales increases and decreases. The reason she includes these variables is that Anderson, Banker, & Janakiraman (2003) find that costs increase more when activity rises than they decrease when activity falls by an equivalent amount.

$$UE\_CE_t=\delta_1+\delta_1 NegDCO_t+\delta_2 PosDCO_t+\delta_3 SIZE_t+\varepsilon \quad (3)$$

$$UE\_\Delta CE_{t+1}=\lambda_0+\lambda_1 NegDCO_t+\lambda_2 PosDCO_t+\lambda_3 SIZE_t+\varepsilon \quad (4)$$

where:

UE_CE_t=	Unexpected core earnings, calculated as the difference between reported and predicted core earnings, where predicted values are estimated from the model 4
$UE\_\Delta CE_{t+1}$=	Unexpected change in core earnings is the difference between actual change in core earnings and predicted change in core earnings in year *t+1*, where predicted values are from the model 5
$NegDCO_t$=	Loss from discontinued operations
$PosDCO_t$=	Gains from discontinued operations
$SIZE_t$=	Natural Logarithm of Total Assets$_t$

I expect a positive relationship between unexpected core earnings and losses from discontinued operations.[18] Unexpected core earnings turn to unexpected loss in my sample. The Australian sample is special as the majority of observations are loss-making firms.[19] Thus, the losses from discontinued operations are not multiplied by (-1) as in McVay (2006).

I do not expect a specific sign for the association between unexpected change in core earnings in year *t+1* and losses from discontinued operations in year *t*, because companies' profitability improves after reporting discontinued operations (Lord & Saito, 2017). The unexpected change in core earnings in the following year is unpredictable; it can be calculated as positive or negative. Australian firms, especially those that report losses, could improve their operation and laterally report profits or continue reporting losses. I run models 1/2 and 3/4 in different samples as additional exploratory tests.

I include a *SIZE* variable in Models 3 and 4 to control firm size, as the sample contains companies of all sizes.[20] I assume there might be a tendency for larger firms to use classification shifting more, to report stable profitability.

[18] Unexpected core earnings are calculated as positive in the US data. Thus, McVay (2006) multiplies negative special items by (-1) to capture a positive relationship between unexpected core earnings and special items.
[19] 63% of the observations report losses as income after tax.
[20] Previous studies (McVay, 2006; Barua, et al., 2010) cut small firms.

5.2.2 Material Discontinued Operations

This is an additional test for firms with material discontinued operations. The idea behind it is that managers might classify core expenses as discontinued operations when they already recognise discontinued operations plus additional core expenses. There is a no chance to create discontinued operations in the income statement if discontinued operations are not recognised in the financial year because of the limitation of the discontinued operations definition.[21] Thus, it might lead managers to report material discontinued operations as the sum of original discontinued operations and manipulated core expenses. The samples with material discontinued operations are selected observations that are over the absolute percentage of 5, 10, 20, 40 and 50 in DCO/CE.

5.2.3 Serial vs Non-Serial Discontinued Operations

This is the test employed by Barau et al (2010). They use it to provide evidence that classification shifting is used not only for serial recognisers but for one-time recognisers. They find that firms reporting discontinued operations only once during the period also engage in classification shifting. Firms with serial discontinued operations might repeatedly use classification shifting as a manipulative tool. In the test, serial recognisers are considered as firms consecutively reporting discontinued operations twice or more during the test period. Otherwise, they are considered non-serial. Serial and Material is a sub-test for firms that consecutively report material discontinued operations twice or more times in the test period.

5.2.4 Benchmark Testing

Hypotheses 2 and 3 predict that managers use discontinued operations to avoid losses and/or earnings decrease. Benchmark tests are undertaken when discontinued operations are used for classification shifting, in other words, the variable *NegDCO* is significant for both Models 3 and 4. I use the following models to examine whether classification shifting using discontinued operations is in engaged to meet or beat certain earnings benchmarks:

[21] Discontinued operations represent a separate major line of business or geographical area of operations.

$$UE\_CE_t = \vartheta_0 + \vartheta_1 NegDCO_t + \vartheta_2 PosDCO_t + \vartheta_3 M\&B_t +$$
$$+ \vartheta_4 NegDCO_t * M\&B_t + \vartheta_5 PosDCO_t * M\&B_t + \Upsilon_6 SIZE_t + \varepsilon \quad (5)$$

$$UE\_\Delta CE_{t+1} = \Upsilon_0 + \Upsilon_1 NegDCO_t + \Upsilon_2 PosDCO_t + \Upsilon_3 M\&B_t +$$
$$+ \Upsilon_4 NegDCO_t * M\&B_t + \Upsilon_5 PosDCO_t * M\&B_t + \Upsilon_6 SIZE_t + \varepsilon \quad (6)$$

where:

$M\&B_t$ is an indicator variable taking on a value of 1 if the firm-year observation meets or beats one of two benchmarks.

The first benchmark is to avoid losses. $M\&B_t$ =1 if the observation has positive continuing income before discontinued operations, and 0 otherwise.

The second earnings benchmark is to avoid earnings decreases. $M\&B_t$ =1 if the observation has a postive continuing income change from the prior year's continuing income.

5.2.5 Sample Scaling and Criteria

For the classification shifting investigation, one-year lag and one-year-ahead data are required. For inclusion in the final sample, each firm-year needs to have income from continuing operations, and total assets in year *t+1*, *t* and *t-1*. There are 12579 firm-year observations with those variables in three consecutive years.[22] To reduce the influence of outliers on the estimated parameters, I ran the outlier test of Cook's distance (D) for all models. By using the guideline D>0.85 (i.e. more than two variables provided n>15 observations), I dropped observations with more than 0.85 Cook's distance, as each model has three and more predictors.[23] Under this restriction, the available samples are reduced by 0.5-3 percent of the total observations.

[22] As classification shifting study requires three consecutive years' data, available data for classification shifting is less than the data for prediction in chapter 4, where two consecutive years' data, 14,491 firm-year observations are required.

[23] Cook's distance should be assessed by the following guideline (McDonald, 2002):
For datasets with n>15, we can consider points as influential:
if D_i > 0.7 for p=2, (one predictor)
if D_i > 0.8 for p=3, (two predictors)
and if D_i > 0.85 for p>3, (more than 3 predictors).

5.3 Results

5.3.1 Descriptive Statistics for Classification Shifting

Table 16 provides descriptive statistics for the variables used in the analyses of classification shifting. Means and medians of core earnings and accruals are all negative for full and DCO samples. Both samples tend to have more loss-making than profit-making firms. Panel A presents descriptive statistics for the full sample. Means and medians of total assets are approximately 2834M and 24M respectively, and the standard deviation (34268M). Panel B reports descriptive statistics for the DCO sample. Means and medians of total assets are approximately 2172M and 39M respectively, and standard deviation (23943M). These figures reflect the inclusion of Australian firms quite different in size.

Table 16 Descriptive Statistics for Classification Shifting

Panel A: Descriptive Statistics for the Full Sample, N=12516

Variables	Mean	Std. Deviation	Minimum	Percentiles			Maximum
				25	50	75	
CE_{t+1}	-0.384	2.722	-93.708	-0.362	-0.081	0.045	84.180
CE_t	-0.333	1.640	-43.961	-0.353	-0.080	0.047	35.274
CE_{t-1}	-0.463	3.120	-97.682	-0.376	-0.084	0.050	84.180
ACC_{t+1}	-0.157	1.936	-69.916	-0.174	-0.049	0.007	86.448
ACC_t	-0.136	1.143	-39.581	-0.163	-0.045	0.010	39.223
ACC_{t-1}	-0.149	2.282	-73.063	-0.164	-0.043	0.014	86.448
$\Delta TA_{t,t-1}$	0.580	4.978	-1.000	-0.139	0.037	0.304	302.709
$\Delta TA_{t-1,t-2}$	1.807	23.031	-0.999	-0.119	0.059	0.391	1350.000
$\Delta CE_{t,t+1}$	-0.050	2.957	-92.528	-0.124	-0.003	0.086	85.338
$\Delta CE_{t,t-1}$	0.130	3.314	-84.935	-0.110	0.000	0.104	97.367
$Neg\Delta TA_{t,t-1}$	-0.112	0.203	-1.000	-0.139	0.000	0.000	0.000
$Neg\Delta TA_{t-1,t-2}$	-0.102	0.192	-0.999	-0.119	0.000	0.000	0.000
$UE\text{-}CE_t$	0.000	1.113	-37.507	-0.075	0.046	0.211	27.292
$UE\_\Delta CE_{t+1,t}$	0.000	1.537	-87.384	-0.110	0.007	0.219	29.171
$NegDCO_t$	-0.014	0.126	-6.412	0.000	0.000	0.000	0.000
$PosDCO_t$	0.013	0.281	0.000	0.000	0.000	0.000	24.438
$SIZE_t$	7.520	1.071	3.262	6.812	7.372	8.139	11.946
TA in millions	2834	34268	0	6	24	138	883301

Continued…

Panel B: Descriptive Statistics for the DCO Sample, N=1625

Variables	Mean	Std. Deviation	Minimum	Percentiles			Maximum
				25	50	75	
CE_{t+1}	-0.214	0.912	-18.447	-0.247	-0.044	0.044	4.450
CE_t	-0.150	0.468	-7.747	-0.216	-0.038	0.037	3.816
CE_{t-1}	-0.213	0.688	-11.738	-0.273	-0.048	0.042	4.091
ACC_{t+1}	-0.094	0.759	-17.308	-0.130	-0.037	0.022	5.379
ACC_t	-0.053	0.401	-6.345	-0.124	-0.038	0.023	5.115
ACC_{t-1}	-0.104	0.516	-8.586	-0.146	-0.045	0.014	4.530
$\Delta TA_{t,t-1}$	0.174	1.326	-0.996	-0.252	-0.036	0.154	15.483
$\Delta TA_{t-1,t-2}$	0.341	1.966	-0.982	-0.191	0.000	0.234	39.209
$\Delta CE_{t,t+1}$	-0.064	0.959	-18.360	-0.106	0.000	0.068	7.501
$\Delta CEt,t\text{-}_1$	0.063	0.693	-4.618	-0.083	0.001	0.103	11.148
$Neg\Delta TA_{t,t-1}$	-0.166	0.242	-0.996	-0.252	-0.036	0.000	0.000
$Neg\Delta TA_{t-1,t-2}$	-0.130	0.205	-0.982	-0.191	0.000	0.000	0.000
$UE\text{-}CE_t$	0.000	0.267	-2.413	-0.058	0.018	0.105	1.357
$UE\_\Delta CE_{t+1,t}$	0.000	0.432	-5.494	-0.067	0.008	0.124	5.256
$NegDCO_t$	-0.094	0.262	-5.370	-0.060	-0.004	0.000	0.000
$PosDCO_t$	0.052	0.249	0.000	0.000	0.000	0.010	3.971
$SIZE_t$	7.724	1.117	4.544	6.941	7.590	8.356	11.946
TA in millions	2172	23914	0	9	39	227	883301

CE_t	Core earnings (before DCO), calculated as ($Sales_t$-Operating $Expenses_t$-Tax_t)/Total $Assets_t$
ACC_t	Accruals, calculated as (Net income before discontinued $operations_t$ -Cash from $operations_t$)/Total $Assets_{t-1}$
$\Delta TA_{t+1,t}$	Percentage change in Total Assets, calculated as (Total $Assets_{t+1}$–Total $Assets_t$)/Total $Assets_t$
$\Delta CE_{t+1,t}$	Change in core earnings, calculated as CE_{t+1}-CE_t
UE_CE_t	Unexpected core earnings measured as the difference between reported and predicted core earnings, where predicted values are estimated from the following equation: $CE_t = \alpha_0+\alpha_1 CE_{t-1}+\alpha_2 ACC_t+\alpha_3 ACC_{t-1} +\alpha_5 \Delta TA_{t,t-1} + \alpha_6 Neg\Delta TA_{t,t-1} +e_t$
$UE\_\Delta CE_{t+1}$	Unexpected change in core earnings is the difference between actual change in core earnings and predicted change in core earnings, where predicted values are estimated from the following equation: $\Delta CE_{t+1,t} = \beta_0+\beta_1\Delta CE_{t,t-1} +\beta_2 CE_t +\beta_3 ACC_{t+1}+ \beta_4 ACC_t + \beta_6 \Delta TA_{t+1,t} + \beta_7 Neg\Delta TA_{t,t-1} + \nu_t$
$NegDCO_t$	If losses from discontinued operations, and otherwise 0
$PosDCO_t$	If gains from discontinued operations, and otherwise 0
$SIZE_t$	Natural logarithm of Total $Assets_t$

Table 17 provides the correlation matrix presenting Spearman (left) Pearson (right) correlation coefficients for the full sample. The results indicate that core earnings are correlated with all independent variables such as CE_{t-1}, ACC_t, ACC_{t-1}, $\Delta TA_{t,t-1}$, and $Neg\Delta TA_{t,t-1}$ in the core earnings model. Unexpected core earnings and unexpected change in core earnings are correlated with losses from discontinued operations in the Spearman

side. Table 18 reports Spearman and Pearson correlations among variables used in the DCO sample. Results are the similar to those in full sample. All variables are correlated with one-year-ahead core earnings. Most importantly, results show that *UE_CE* is positively correlated with *NegDCO*, whereas *UE_*Δ*CE* is negatively correlated with *NegDCO*, suggesting that managers use discontinued operations to increase core earnings.

5.3.2 Expected Core Earnings and Expected Change in Core Earnings

The forecasted core earnings and change in core earnings in year *t+1* are estimated for both the full and DCO samples. Both samples are pooled by year because the coefficients are different over the years and also each year has a sufficient number of observations to estimate for all intended models. I included 10 dummy variables for industry and left the material industry as the base industry in the intercept.

Tables 19 and 20 report regression results of models (1) and (2) for the full sample and the full sample by year. Table 19 reports the results of model (1), expected core earnings in year *t*. The coefficient on current accruals is a stronger predictor (0.975) than lagged core earnings (0.095). Current accruals tend to be more persistent than CE, a finding which is inconsistent with those of McVay (2006). It is possible that extreme accruals could be due to accrual management. For the pooled-year samples, the adjusted R^2 ranges are from 44.41% for the year 2013 to 86.89% for 2008. Table 20 reports the results of model (2). The majority of variables is statistically significant. The coefficient of core earnings is negatively associated with the change in core earnings, consistent with the results of McVay (2006). The adjusted R^2 ranges are relatively stable, from 72.52 % for the pooled data 2014, to 89.89% for the pooled data 2013.

Table 17 Spearman (left) and Pearson (right) Correlations, Full Sample N=12516

	CE_{t+1}	CE_t	CE_{t-1}	ACC_{t+1}	ACC_t	ACC_{t-1}	$\Delta TA_{t,t-1}$	$\Delta TA_{t-1,t-2}$	$\Delta CE_{t,t+1}$	$\Delta CE_{t,t-1}$	$Neg\Delta TA_{t,t-1}$	$Neg\Delta TA_{t-1,t-2}$	UE-CE_t	UE_$\Delta CE_{t+1,t}$	$NegDCO_t$	$PosDCO_t$	SIZE
CE_{t+1}	1.000	.152**	.079**	.805**	.074**	.035**	0.004	0.000	.836**	0.001	.196**	.129**	.096**	.565**	-0.004	-0.005	.225**
CE_t	.703**	1.000	.141**	.057**	.701**	.069**	-.312**	0.000	-.415**	.362**	.061**	.224**	.678**	0.000	.027**	-.020*	.229**
CE_{t-1}	.632**	.712**	1.000	.047**	.071**	.666**	-.057**	-.439**	-0.006	-.872**	.051**	0.011	0.000	0.000	0.006	0.001	.147**
ACC_{t+1}	.534**	.242**	.195**	1.000	0.012	.023*	-0.002	-0.003	.709**	-0.016	.060**	.047**	.048**	0.000	-.044**	0.005	.084**
ACC_t	.251**	.515**	.233**	.269**	1.000	.047**	-.018*	0.000	-.321**	.280**	.066**	.068**	0.000	0.000	-0.002	-0.003	.095**
ACC_{t-1}	.201**	.248**	.501**	.184**	.260**	1.000	-.027**	.034**	-0.006	-.593**	.024**	.022*	0.000	-0.010	0.000	0.002	.050**
$\Delta TA_{t,t-1}$	.188**	.221**	.100**	.088**	.196**	.044**	1.000	0.002	.176**	-.101**	.117**	-.093**	-.405**	0.000	0.009	0.010	-0.015
$\Delta TA_{t-1,t-2}$	.113**	.140**	.135**	.020*	.074**	.146**	.140**	1.000	0.000	.413**	0.005	.052**	0.000	.019*	0.007	-0.003	-.021*
$\Delta CE_{t,t+1}$	.343**	-.270**	-.061**	.383**	-.283**	-.048**	.105**	-.029**	1.000	-.200**	.146**	-0.006	-.288**	.520**	-.019*	0.006	.080**
$\Delta CE_{t,t-1}$	.075**	.286**	-.321**	.061**	.351**	-.293**	.085**	.151**	-.260**	1.000	-.018*	.100**	.336**	0.000	0.007	-0.011	-.025**
$Neg\Delta TA_{t,t-1}$	.293**	.358**	.224**	.113**	.256**	.090**	.906**	.144**	.064**	.113**	1.000	.181**	-.040**	0.000	.132**	-0.014	.408**
$Neg\Delta TA_{t-1,t-2}$	.236**	.268**	.306**	.052**	.107**	.223**	.139**	.890**	-.026**	.084**	.192**	1.000	0.000	.073**	.093**	-.060**	.363**
UE-CE_t	.229**	.306**	.167**	-.019*	-.132**	-.134**	-.107**	-.402**	-.112**	.143**	-.056**	-.409**	1.000	-.021*	0.014	-0.010	.097**
UE_$\Delta CE_{t+1,t}$	.105**	-.035**	.078**	-.247**	-.253**	-.085**	-.501**	-0.015	.153**	-.113**	-.529**	-0.010	.260**	1.000	0.014	-0.008	.122**
$NegDCO_t$	-0.001	-0.001	0.013	-.041**	-.049**	-0.007	.119**	.069**	-0.002	-.026**	.130**	.073**	-.029**	-.085**	1.000	0.005	.086**
$PosDCO_t$	.056**	.062**	.058**	.029**	0.007	-0.004	-.028**	-.053**	0.008	-0.003	-.020*	-.039**	.058**	.027**	.069**	1.000	-.032**
$SIZE_t$	.603**	.629**	.616**	.180**	.208**	.202**	.236**	.203**	.042**	.024**	.347**	.328**	.118**	0.016	-0.005	.078**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 18 Spearman (left) and Pearson (right) Correlations, DCO Sample N=1625

	CE_{t+1}	CE_t	CE_{t-1}	ACC_{t+1}	ACC_t	ACC_{t-1}	$\Delta TA_{t,t-1}$	$\Delta TA_{t-1,t-2}$	$\Delta CE_{t,t+1}$	$\Delta CE_{t,t-1}$	$Neg\Delta TA_{t,t-1}$	$Neg\Delta TA_{t-1,t-2}$	$UE\text{-}CE_t$	$UE\_\Delta CE_{t+1,t}$	$NegDCO_t$	$PosDCO_t$	SIZE
CE_{t+1}	1.000	.155**	.157**	.827**	-.067**	.067**	0.029	0.013	.876**	-.051*	.184**	.167**	.147**	.473**	.104**	-.102**	.292**
CE_t	.634**	1.000	.329**	-0.006	.671**	.060*	-.242**	-.053*	-.340**	.349**	.110**	.188**	.571**	0.000	.250**	-0.042	.329**
CE_{t-1}	.560**	.656**	1.000	0.035	.098**	.769**	-.079**	-.506**	-0.011	-.770**	.161**	.129**	0.000	0.000	.130**	-0.025	.316**
ACC_{t+1}	.426**	.101**	0.043	1.000	-0.048	0.048	0.002	0.013	.791**	-0.039	-0.010	0.045	0.022	0.000	-0.016	-.084**	.071**
ACC_t	.060*	.396**	.063*	.191**	1.000	0.046	-.065**	-.068**	-.392**	.355**	0.029	-.132**	0.000	0.000	-.064*	0.018	-0.026
ACC_{t-1}	.098**	.140**	.454**	.127**	.198**	1.000	0.005	-.321**	0.034	-.722**	.081**	.121**	0.000	-0.033	0.017	-0.015	.107**
$\Delta TA_{t,t-1}$	.169**	.229**	.192**	0.006	.101**	.104**	1.000	.060*	.146**	-.085**	.359**	-.076**	-.232**	0.000	-0.019	.132**	0.038
$\Delta TA_{t-1,t-2}$	.138**	.113**	.250**	-0.015	-0.033	.217**	.156**	1.000	0.038	.466**	0.037	.256**	0.000	0.030	0.032	-0.033	-0.008
$\Delta CE_{t,t+1}$	.415**	-.278**	-.059*	.382**	-.377**	-.050*	.063*	0.028	1.000	-.219**	.122**	.067**	-.139**	.450**	-0.023	-.076**	.117**
$\Delta CE_{t,t-1}$	.059*	.273**	-.400**	.064**	.373**	-.392**	-0.018	-0.031	-.249**	1.000	-.085**	-0.001	.386**	0.000	0.040	-0.004	-.092**
$Neg\Delta TA_{t,t-1}$	.238**	.312**	.278**	0.007	.117**	.121**	.957**	.167**	0.043	-0.017	1.000	.183**	-0.048	0.000	.242**	0.008	.437**
$Neg\Delta TA_{t-1,t-2}$	.216**	.206**	.366**	-0.014	-0.028	.245**	.160**	.936**	0.017	-.074**	.198**	1.000	0.000	0.029	.194**	-.136**	.376**
$UE\text{-}CE_t$	.276**	.414**	.097**	0.039	-0.022	-0.036	-.061*	-.280**	-.148**	.398**	-0.031	-.272**	1.000	-0.041	.280**	-0.009	.165**
$UE\_\Delta CE_{t+1,t}$	.139**	-.090**	-.063*	-.180**	-.058*	-.104**	-.313**	0.005	.330**	-0.027	-.337**	-0.022	-0.001	1.000	-0.025	-0.039	.101**
$NegDCO_t$	.234**	.268**	.283**	-0.039	-.107**	-0.007	.220**	.061*	0.030	-.060*	.261**	.103**	.109**	-.128**	1.000	.076**	.298**
$PosDCO_t$	.073**	.100**	.103**	-0.017	-.075**	-0.027	.129**	-0.023	0.015	-0.048	.132**	-0.004	.081**	-.103**	.839**	1.000	-.106**
$SIZE_t$	.534**	.546**	.603**	0.016	-0.032	.106**	.277**	.242**	.070**	-.069**	.355**	.338**	.136**	0.004	.316**	.075**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 19 Regression results of Expected Core Earnings, Dependent Variable CE_t, Full Sample

Independent Variable	Full Sample	Full Sample by Year								
		2016	2015	2014	2013	2012	2011	2010	2009	2008
(Constant)	-0.067	0.07	-0.06	-0.081	-0.132	-0.031	-0.042	-0.154	-0.099	-0.074
	-3.928***	2.744**	-4.134***	-5.832***	-3.415***	-1.053	-3.008**	-4.735***	-3.484***	-3.017**
CE_{t-1}	0.095	0.454	0.372	0.151	0.17	0.733	0.329	0.032	0.169	0.296
	17.318***	19.046***	21.119***	18.964***	8.502***	17.694***	25.876***	4.616***	11.389***	16.690***
ACC_t	0.975	1.073	0.817	0.967	1.137	1.15	0.942	0.973	1.038	1.022
	111.231***	65.738***	40.186***	39.502***	27.868***	85.208***	61.712***	29.833***	40.273***	67.455***
ACC_{t-1}	-0.066	-0.247	-0.357	-0.101	-0.075	-0.813	-0.214	-0.033	-0.17	-0.161
	-9.804***	-8.369***	-15.076***	-7.770***	-3.201***	-15.266***	-12.787***	-3.637***	-8.248***	-7.847***
$\Delta TA_{t-1, t-2}$	0.005	0.012	0.036	0.009	0.028	0.037	0.025	0.001	0.007	0.023
	9.637***	2.256**	15.246***	8.354***	5.673***	3.533***	16.721***	3.990***	3.263***	9.591***
$Neg\Delta TA_{t-1, t-2}$	1.44	0.795	0.703	0.537	1.582	0.886	0.408	1.589	1.458	0.729
	27.494***	11.148***	15.443***	10.009***	11.273***	11.511	9.257***	12.980***	15.020***	8.794***
Consumer Discretionary	0.203	0.022	0.139	0.152	0.3	0.099	0.104	0.253	0.215	0.119
	5.248***	0.39	4.111***	4.631***	3.290***	1.562	3.447***	3.632***	3.772***	2.470**
Consumer Staples	0.1	-0.051	0.028	0.033	0.138	0.033	0.062	0.084	0.12	0.032
	1.602	-0.543	0.494	0.6	0.905	0.32	1.31	0.774	1.329	0.421
Energy	0.021	-0.038	0.037	-0.013	0.108	0.081	0.001	0.037	-0.025	0.05
	0.654	-0.801	1.339	-0.47	1.451	1.594	0.037	0.593	-0.472	1.067
Financials	0.184	-0.077	0.136	0.107	0.253	0.164	0.074	0.256	0.157	0.088
	4.749***	-1.328	4.096***	3.280***	2.807**	2.649**	2.452**	3.656***	2.726**	1.759*
Health Care	-0.14	-0.289	0.001	-0.087	-0.024	0.043	-0.024	0.014	-0.012	-0.067
	-3.560***	-4.915***	0.023	-2.613**	-0.26	0.692	-0.771	0.194	-0.21	-1.316
Industrials	0.082	0.007	0.062	0.128	0.258	0.118	0.038	0.201	0.214	0.15
	2.328**	0.128	2.019**	4.318***	3.157**	2.120**	1.387	3.147**	3.949***	3.141**
Information Technology	-0.055	-0.222	0.017	-0.004	-0.073	0.054	0.012	0.138	0.054	0.065
	-1.382	-3.866***	0.502	-0.104	-0.783	0.841	0.398	1.904**	0.883	1.275
Real Estate	0.172	-0.01	0.105	0.122	0.291	0.151	0.077	0.221	0.087	0.113
	2.939**	-0.12	2.083**	2.437**	2.103**	1.594	1.664*	2.151**	1.042	1.517
Telecommunication Services	0.296	0.113	-0.024	0.184	0.342	0.446	0.118	0.421	0.38	0.33
	2.801**	0.737	-0.253	2.011**	1.378	2.664**	1.425	2.271**	2.499**	2.417**
Utilities	-0.05	0.042	0.01	0.018	0.318	0.065	-0.001	0.051	0.277	-0.056
	-0.525	0.272	0.112	0.219	1.421	0.425	-0.018	0.288	1.974**	-0.47
F- Stat	977.303***	336.137***	213.444***	161.667***	79.675***	584.616***	378.831***	74.676***	158.368***	407.336***
R^2	53.92%	74.11%	65.55%	60.72%	44.41%	85.98%	80.74%	48.68%	69.36%	86.89%
Number of obs	12516	1757	1676	1560	1478	1428	1353	1166	1044	921

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

CE_t= Core Earnings, calculated as net profit before discontinued operations/TA_{t-1}
ACC_t = Operating Accruals, calculated as (net income before discontinued operations-cash from operations$_t$)/TA_{t-1}
ΔTA_t= Change in Total Assets, calculated as (TA_t-TA_{t-1})/TA_{t-1}
$Neg\Delta TA_t$= Percent change in TA, calculated as (ΔTA_t) if ΔTA_t, is less than 0 and 0 otherwise
Industries= Dummy variable=1, 0 otherwise

Table 20 Regression results of Expected Change in Core Earnings, Dependant Variable $\Delta CE_{t+1,t}$

Independent Variable	Full Sample	Full Sample by Year								
		2016	2015	2014	2013	2012	2011	2010	2009	2008
(Constant)	0.066	0.13	0.109	-0.031	-0.078	-0.082	0.002	-0.027	-0.07	-0.022
	2.765**	3.321***	4.691***	-2.330**	-4.628***	-2.272**	0.061	-1.769*	-2.780**	-0.904
ΔCE_{t-1}	-0.017	-0.135	-0.04	-0.017	-0.027	-0.046	-0.04	0	-0.017	-0.032
	-3.745***	-4.627***	-3.237***	-3.089**	-5.904***	-1.873*	-2.266**	-0.016	-2.419**	-2.990**
CE_t	-0.77	-0.453	-0.33	-0.434	-0.724	-0.582	-0.148	-0.6	-0.483	-0.498
	-57.192***	-11.798***	-10.327***	-19.142***	-57.100***	-15.569***	-3.191***	-39.494***	-18.886***	-16.555***
ACC_{t+1}	1.108	1.213	1.05	0.851	1.024	1.055	1.107	0.861	0.883	0.993
	155.184***	86.785***	70.561***	43.859***	59.378***	26.261***	73.451***	42.381***	36.823***	41.508***
ACC_t	-0.086	-0.32	-0.422	-0.537	-0.202	-0.328	-0.774	-0.253	-0.446	-0.438
	-4.839***	-6.917***	-10.036***	-17.126***	-8.933***	-7.977***	-13.275***	-12.966***	-12.773***	-12.466***
ΔTA_{t-1}	0.016	0.058	0.015	0.054	0.032	0.044	0.006	0.032	0.034	0.025
	5.363***	4.218***	1.940*	7.305***	9.349***	5.752***	0.394	15.748***	6.589***	6.239***
$Neg\Delta TA_{t-1}$	1.832	1.292	0.751	0.64	0.454	1.304	0.84	0.4	0.84	1.203
	26.523	12.147***	11.521***	14.736***	7.402***	10.142***	10.561***	8.824***	9.376***	14.641***
Consumer Discretionary	0.087	-0.237	-0.025	0.103	0.138	0.206	0.074	0.082	0.122	0.113
	1.621	-2.753**	-0.477	3.460***	3.496***	2.460**	1.154	2.642**	2.439**	2.347**
Consumer Staples	-0.036	-0.24	-0.078	0.05	-0.016	0.148	0.063	0.044	0.036	0.067
	-0.42	-1.708*	-0.901	1.026	-0.244	1.099	0.623	0.901	0.451	0.886
Energy	-0.058	0.018	-0.038	0.05	0.003	0.066	0.088	-0.024	0.021	-0.057
	-1.289	0.255	-0.906	2.106	0.089	0.973	1.649*	-0.872	0.457	-1.223
Financials	0.06	-0.11	-0.123	0.109	0.088	0.196	0.152	0.037	0.099	0.05
	1.126	-1.257	-2.386**	3.719***	2.267**	2.379**	2.369	1.184	1.958**	1
Health Care	-0.119	-0.088	-0.244	0.032	-0.033	-0.068	0.047	-0.037	0.013	0.077
	-2.182**	-0.987	-4.605***	1.068	-0.821	-0.814	0.726	-1.177	0.258	1.516
Industrials	0.005	-0.056	-0.024	0.033	0.098	0.178	0.091	0.033	0.089	0.101
	0.113	-0.712	-0.498	1.236	2.777**	2.409**	1.57	1.161	1.884*	2.118**
Information Technology	-0.164	-0.064	-0.148	0.038	0.045	-0.037	0.025	0.005	0.108	0.008
	-3.004**	-0.739	-2.859**	1.235	1.111	-0.428	0.385	0.15	2.050*	0.152
Real Estate	0.064	-0.071	-0.06	0.086	0.113	0.211	0.137	0.06	0.078	-0.001
	0.789	-0.554	-0.771	1.905**	1.897*	1.684*	1.4	1.297	1.075	-0.019
Telecommunication Services	0.248	0.169	0.085	-0.098	0.169	0.187	0.42	0.085	0.177	0.341
	1.702*	0.73	0.593	-1.197	1.58	0.841	2.402**	1.033	1.336	2.513**
Utilities	-0.021	0.092	-0.191	0.039	0.034	0.339	0.016	0.033	-0.14	0.246
	-0.158	0.398	-1.46	0.546	0.353	1.675*	0.101	0.421	-1.148	2.090**
F- Stat	2111.655***	604.026***	359.522***	258.085***	821.980***	342.603***	381.225***	577.754***	218.463***	440.431***
R^2	72.96%	84.60%	77.40%	72.52%	89.89%	79.30%	81.82%	88.79%	76.94%	88.43%
Number of obs	12516	1757	1676	1560	1478	1428	1353	1166	1044	921

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

$\Delta CE_{t=}$ Change in Core Earnings, calculated as CE_t-CE_{t-1}

$CE_{t=}$ Core Earnings, calculated as net profit before discontinued operations/TA_{t-1}

ACC_t = Operating Accruals, calculated as (net income before discontinued operations-cash from operations$_t$)/TA_{t-1}

ΔTA_t= Change in Total Assets, calculated as (TA_t-TA_{t-1})/TA_{t-1}

$Neg\Delta TA_t$= Percent change in TA, calculated as (ΔTA_t) if ΔTA_t, is less than 0 and 0 otherwise

Industries= Dummy variable=1, 0 otherwise

Table 21 Regression results of Expected Core Earnings, Dependent Variable CE_t, DCO Sample

Independent Variable	DCO Sample	DCO sample by Year								
		2016	2015	2014	2013	2012	2011	2010	2009	2008
(Constant)	-0.041	0.052	-0.095	-0.031	-0.014	0.09	-0.037	-0.038	-0.088	-0.09
	-2.917**	2.077**	-3.337***	-1.189	-0.42	2.100**	-1.33	-0.788	-3.021**	-1.53
CE_{t-1}	0.414	0.646	0.58	0.559	0.613	0.773	0.219	0.438	0.592	0.673
	23.361***	12.539***	10.062***	12.354***	12.584***	11.975***	7.478***	6.300***	12.345**	7.765***
ACC_t	0.775	0.957	0.786	0.753	0.979	0.914	0.777	0.661	0.949	1.005
	45.743***	19.381***	14.059***	11.093***	28.933***	13.242***	12.081***	8.307***	19.086***	7.650***
ACC_{t-1}	-0.391	-0.452	-0.599	-0.46	-0.448	-0.734	-0.17	-0.474	-0.476	-0.255
	-18.833***	-6.797***	-8.455***	-6.227***	-5.649***	-9.369***	-5.686***	-5.952***	-7.918***	-1.898*
$\Delta TA_{t-1, t-2}$	0.028	-0.055	0.071	0.039	0.009	0.008	0.017	0.048	0.017	0.108
	6.638***	-1.403	4.655***	2.625**	0.509	0.413	2.818**	2.453**	1.614	2.615**
$Neg\Delta TA_{t-1, t-2}$	0.465	0.449	0.288	0.219	0.356	0.514	0.183	0.438	0.112	0.557
	12.891***	5.700***	3.153**	2.603**	3.526***	5.358***	2.658**	3.289***	1.066	3.362***
Consumer Discretionary	0.104	-0.022	0.154	0.086	0.067	-0.021	0.046	0.049	0.143	0.175
	4.508***	-0.556	3.208**	2.084**	1.199	-0.322	0.997	0.617	3.421***	2.249**
Consumer Staples	0.064	0.027	0.113	0.033	-0.045	0.003	0.046	-0.082	0.134	0.13
	1.720*	0.402	1.721*	0.454	-0.532	0.028	0.605	-0.567	1.859*	1.222
Energy	-0.026	-0.028	0.053	-0.014	0.05	-0.083	-0.012	-0.252	0.071	0.294
	-1.086	-0.759	1.116	-0.319	0.921	-1.339	-0.264	-3.064**	1.359	3.119**
Financials	0.061	0.014	0.132	-0.003	-0.009	0.021	-0.025	-0.074	0.128	0.173
	2.134**	0.331	2.393**	-0.063	-0.127	0.259	-0.448	-0.672	2.220**	1.605
Health Care	-0.014	-0.041	0.009	0.085	0.059	-0.051	-0.214	-0.048	-0.072	0.039
	-0.488	-0.793	0.156	1.672*	0.85	-0.686	-3.691***	-0.496	-1.054	0.341
Industrials	0.067	-0.024	0.102	0.038	0.04	-0.019	0.042	0.01	0.103	0.133
	3.041**	-0.621	2.348**	1.03	0.802	-0.322	1.003	0.132	2.408**	1.542
Information Technology	0.004	-0.104	0.008	-0.007	0.001	-0.184	-0.001	0.07	0.06	0.175
	0.153	-2.060**	0.171	-0.166	0.011	-2.004	-0.021	0.848	1.334	1.985**
Real Estate	0.112	0.066	0.115	0.042	0.068	0.027	0.081	0.094	0.117	0.288
	3.308***	1.054	1.601	0.753	0.89	0.322	1.318	0.831	1.751*	2.143**
Telecommunication Services	-0.004	0.294	0.056	-0.1	-0.231	0.113	-0.055	0	0.303	-0.053
	-0.075	3.353***	0.574	-0.835	-1.456	0.893	-0.521	0	3.249**	-0.278
Utilities	0.022	0	-0.138	0.103	0.09	-0.12	0.021	0.017	0.082	0.042
	0.286	0	-0.715	0.617	0.571	-0.767	0.168	0.06	0.543	0.167
F- Stat	221.465***	50.380***	27.564***	22.232***	91.599***	26.137***	18.993***	12.461***	51.837***	19.538***
R^2	67.07%	76.03%	65.81%	60.96%	87.17%	67.57%	59.59%	52.70%	85.15%	72.40%
Number of obs	1625	219	208	205	201	182	184	145	134	107

*,**,*** Indicate at the 10, 5, and 1 percent levels, respect

$CE_{t=}$ Core Earnings, calculated as net profit before discontinued operations/TA_{t-1}
ACC_t = Operating Accruals, calculated as (net income before discontinued operations-cash from operations$_t$)/TA_{t-1}
ΔTA_t= Change in Total Assets, calculated as (TA_t-TA_{t-1})/TA_{t-1}
$Neg\Delta TA_t$= Percent change in TA, calculated as (ΔTA_t) if ΔTA_t, is less than 0 and 0 otherwise
Industries= Dummy variable=1, 0 otherwise

Table 22 Regression results of Expected Change in Core Earnings, Dependant Variable $\Delta CE_{t+1,t}$

Independent Variable	DCO Sample	DCO sample by Year								
		2016	2015	2014	2013	2012	2011	2010	2009	2008
(Constant)	0.022	0.027	0.070	-0.050	-0.035	-0.033	0.198	-0.030	0.006	-0.125
	0.947	0.808	2.016**	-1.948*	-1.088	-0.865	2.308**	-0.978	0.211	-2.976**
ΔCEt_{t-1}	-0.038	-0.052	-0.189	-0.056	-0.072	0.000	-0.006	-0.006	-0.016	-0.096
	-2.204**	-0.903	-5.834***	-1.399	-1.408	-0.007	-0.130	-0.296	-0.290	-1.409
CEt	-0.405	-0.316	-0.291	-0.353	-0.453	-0.513	0.249	-0.630	-0.432	-0.595
	-11.561***	-4.776***	-4.308***	-6.232***	-7.816***	-8.562***	1.240	-13.518***	-7.781***	-10.506***
ACC_{t+1}	0.984	0.921	1.036	0.935	1.121	0.930	1.075	0.873	0.853	0.789
	68.900***	15.441***	13.992***	18.805***	24.023***	27.372***	28.546***	16.659***	16.411***	18.298***
ACCt	-0.512	-0.684	-0.574	-0.551	-0.520	-0.366	-1.059	-0.225	-0.528	-0.374
	-13.536***	-7.302***	-7.515***	-6.454***	-7.064***	-4.368***	-4.359***	-4.064***	-6.832***	-3.560***
$\Delta TAt_{,t-1}$	0.024	0.050	0.027	0.055	0.023	-0.008	0.077	0.009	0.010	0.016
	2.621**	1.926**	1.707*	2.930**	1.769*	-0.651	1.537	1.130	0.747	1.015
$Neg\Delta TAt_{,t-1}$	0.539	0.328	0.363	0.164	0.518	0.194	0.635	0.262	0.205	0.295
	10.771***	4.484***	5.245***	2.218**	5.514***	1.987**	3.931***	3.664***	2.782**	2.256**
Consumer Discretionary	0.086	-0.013	-0.036	0.087	0.170	0.082	-0.077	0.096	0.055	0.201
	2.292**	-0.238	-0.651	2.109**	3.127**	1.304	-0.593	1.930**	1.389	3.515***
Consumer Staples	0.050	0.003	0.022	0.074	0.111	0.008	-0.030	0.041	0.007	0.176
	0.832	0.033	0.292	1.037	1.326	0.085	-0.140	0.451	0.110	2.197**
Energy	-0.007	-0.080	0.022	0.009	0.016	-0.013	-0.075	0.117	0.001	0.097
	-0.177	-1.678*	0.407	0.202	0.312	-0.208	-0.566	2.179**	0.012	1.317
Financials	0.040	-0.045	-0.013	-0.008	0.154	0.156	0.037	0.053	-0.047	0.208
	0.870	-0.797	-0.206	-0.138	2.266	1.880*	0.241	0.783	-0.868	2.609**
Health Care	-0.128	0.037	-0.152	0.085	0.034	0.085	-0.306	-0.131	-0.111	0.056
	-2.711**	0.548	-2.357**	1.639	0.513	1.105	-1.812*	-2.062**	-1.783*	0.645
Industrials	0.015	-0.014	-0.041	0.068	0.105	0.068	-0.232	0.108	-0.002	0.169
	0.426	-0.279	-0.826	1.832*	2.146**	1.138	-1.867	2.355**	-0.057	2.606**
Information Technology	-0.039	-0.143	-0.029	0.034	0.089	-0.096	-0.157	0.020	0.016	0.080
	-0.977	-2.214**	-0.557	0.863	1.523	-1.024	-1.139	0.381	0.388	1.215
Real Estate	0.043	0.032	-0.026	0.055	0.073	0.073	-0.007	0.068	0.069	-0.037
	0.780	0.391	-0.316	0.993	0.979	0.867	-0.042	0.947	1.134	-0.358
Telecommunication Services	0.102	0.061	0.056	0.001	-0.033	-0.075	0.169	0.000	0.135	0.287
	1.146	0.515	0.506	0.008	-0.210	-0.590	0.566	0.000	1.602	2.115**
Utilities	-0.261	0.000	-4.032	0.097	0.157	-0.054	-0.035	0.021	-0.047	0.116
	-2.134**	0.000	-11.949***	0.579	1.014	-0.375	-0.097	0.117	-0.339	0.620
F- Stat	395.300***	37.459***	27.731***	33.063***	121.269***	63.116***	52.815***	33.575***	50.027***	54.428***
R^2	67.07%	71.50%	67.39%	71.55%	90.59%	84.59%	81.92%	77.24%	85.50%	88.97%
Number of obs	1625	219	208	205	201	182	184	145	134	107

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

$\Delta CE_{t=}$ Change in Core Earnings, calculated as CE_t-CE_{t-1}

$CE_{t=}$ Core Earnings, calculated as net profit before discontinued operations/TA_{t-1}

ACC_t = Operating Accruals, calculated as (net income before discontinued operations-cash from operations$_t$)/TA_{t-1}

ΔTA_t= Change in Total Assets, calculated as (TA_t-TA_{t-1})/TA_{t-1}

$Neg\Delta TA_t$= Percent change in TA, calculated as (ΔTA_t) if ΔTA_t, is less than 0 and 0 otherwise

Industries= Dummy variable=1, 0 otherwise

Tables 21 and 22 provide the results of the models (1) and (2) for the DCO sample. This sample is also pooled by year. Table 21 reports the results of model (1), expected core earnings. Similar to the full sample, the coefficient of current accrual (0.775) is a stronger predictor than the lagged core earnings (0.414). The adjusted R^2 ranges from 52.70% for 2010 to 87.17% for 2013. Table 22 provides the results for the model (2), one-year-ahead expected change in core earnings. The coefficient of one-year-ahead accrual is a stronger predictor (0.984) than other variables to estimate the change in core earnings in year *t+1*. The adjusted R^2 ranges are relatively higher than those of model (1), from 67.39% for 2015, to 90.59% for 2013.

5.3.3 Classification Shifting Results

Table 23 reports classification shifting analysis for the full and the pooled-by-year samples. Panel A reports the regression results of model (3), the association between unexpected core earnings, and losses and gains from discontinued operations. For model (3), the coefficient on $NegDCO_t$ is not significant as expected. Panel B reports the regression results of model (4), association between unexpected change in core earnings, and losses and gains from discontinued operations. The results show that there is no association between them for the full sample and the full sample over years. However, *SIZE* is significant for all samples, indicating that firm size is relevant to forecast future earnings.

Table 24 reports classification shifting analysis for the DCO and the DCO pooled-by-year samples. Panel A reports the regression results of model (3), the association between unexpected core earnings, and losses and gains from discontinued operations. For model (3), the coefficient on $NegDCO_t$ is positive and significant (δ_1 =0.261, p<0.001), as expected. *PosDCO* is negative, but not significant. These findings suggest that classification shifting takes place when firms report losses from discontinued operations.

Panel B reports regression results of model (4), the association between unexpected change in core earnings, and losses and gains from discontinued operations. For model (4), the coefficients on $NegDCO_t$ are negative and significant (δ_1 =-0.096, p<0.05), as expected. These findings suggest that the reversal of the improvements in core earnings in year *t+1* is associated with the reporting of losses from discontinued operations in year *t*.

Table 23 Regressions of Unexpected Core Earnings and Unexpected Change in Core Earnings on Discontinued Operations, Full Sample

Panel A: Dependent Variable = UE_CE_t

Independent Variable	Predicted sign	Full Sample	Full Sample by Year								
			2016	2015	2014	2013	2012	2011	2010	2009	2008
(Constant)		-0.752	-0.339	-0.404	-0.588	-0.789	-0.126	-0.293	-0.805	-0.335	-0.421
		-10.645***	-3.397***	-6.812***	-9.893***	-4.572***	-1.096	-5.499***	-6.040***	-2.964**	-4.508***
$NegDCO_t$	+	0.050	-0.079	0.122	-0.101	-0.454	-0.554	0.041	0.277	-0.180	0.181
		0.640	-0.548	1.292	-0.569	-1.800*	-1.659*	0.467	1.515	-1.053	0.878
$PosDCO_t$	-	-0.028	0.053	0.074	0.084	0.188	0.006	-0.033	0.146	0.357	0.630
		-0.792	0.383	0.404	1.553	0.791	0.051	-0.240	0.536	0.674	1.541
$SIZE_t$		0.100	0.045	0.054	0.077	0.103	0.016	0.039	0.106	0.044	0.056
		10.784***	3.428***	6.922***	9.975***	4.581***	1.075	5.588***	6.137***	2.965**	4.547***
F- Stat		40.011***	3.942**	17.302***	33.587***	7.845***	1.221	10.906***	13.959***	3.258**	8.216***
R^2		0.93%	0.50%	2.84%	5.90%	1.37%	0.05%	2.15%	3.23%	0.65%	2.30%

Panel B: Dependent Variable = $UE\_\Delta CE_{t+1,t}$

Independent Variable	DCO Sample	Full Sample by Year								
		2016	2015	2014	2013	2012	2011	2010	2009	2008
(Constant)	-1.311	-0.897	-0.291	-0.265	-0.745	-1.000	-0.341	-0.300	-0.577	-0.322
	-13.476***	-6.036	-3.162	-4.848***	-10.328***	-6.676***	-3.011**	-5.039***	-5.933***	-3.455***
$NegDCO_t$	0.042	-0.465	-0.258	0.027	-0.135	-1.339	-0.261	0.093	-0.266	-0.290
	0.391	-2.160**	-1.750*	0.169	-1.280	-3.080**	-1.414	1.142	-1.817*	-1.414
$PosDCO_t$	-0.024	0.383	-0.157	0.020	-0.101	-0.063	-0.072	-0.018	0.128	-0.160
	-0.493	1.871*	-0.552	0.393	-1.017	-0.403	-0.248	-0.147	0.280	-0.392
$SIZE_t$	0.174	0.119	0.038	0.035	0.098	0.132	0.045	0.040	0.075	0.043
	13.642***	6.054***	3.172**	4.903***	10.425***	6.695***	3.022**	5.125***	5.960***	3.476***
F- Stat	63.136***	13.779***	4.187**	8.092	36.695***	17.333***	3.431**	9.597***	12.351***	4.534**
R^2	1.47%	2.14%	0.57%	1.35%	6.76%	3.32%	0.54%	2.17%	3.16%	1.14%
Number of obs	12516	1757	1680	1558	1479	1427	1356	1166	1045	924

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

Table 24 Regressions of Unexpected Core Earnings and Unexpected Change in Core Earnings on Discontinued Operations, DCO Sample

Panel A: Dependent Variable = UE_CE_t

Independent Variable	DCO Sample	DCO sample by Year								
		2016	2015	2014	2013	2012	2011	2010	2009	2008
(Constant)	-0.134	-0.090	-0.042	-0.167	0.031	-0.155	-0.199	-0.331	-0.167	-0.093
	-2.801***	-1.123	-0.435	-1.803*	0.295	-1.159	-2.280**	-2.026	-1.589	-0.485
$NegDCO_t$	0.261	-0.058	0.158	0.121	0.216	-0.255	0.164	0.045	-0.027	0.093
	10.231***	-1.203	2.672**	1.188	6.818***	-1.761*	2.779**	0.385	-0.417	0.669
$PosDCO_t$	-0.021	0.023	-0.066	-0.036	0.012	-0.099	-0.122	-0.096	0.154	0.438
	-0.800	0.537	-0.652	-0.763	0.230	-2.075**	-1.510	-0.461	0.912	1.641
$SIZE_t$	0.021	0.011	0.008	0.022	-0.001	0.019	0.029	0.043	0.020	0.011
	3.442***	1.079	0.663	1.952**	-0.095	1.152	2.640**	2.137	1.595	0.462
F- Stat	51.010***	0.657	3.568**	2.686**	16.198***	3.173**	8.788***	1.870	0.993	1.400
R^2	8.46%	-0.47%	3.59%	2.42%	18.57%	3.48%	11.32%	1.78%	-0.02%	1.12%

Panel B: Dependent Variable = $UE\_\Delta CE_{t+1,t}$

Independent Variable	DCO Sample	DCO sample by Year								
		2016	2015	2014	2013	2012	2011	2010	2009	2008
(Constant)	-0.353	-0.174	-0.045	-0.249	-0.291	-0.201	-0.483	-0.300	-0.197	-0.248
	-4.398***	-1.694	-0.410	-2.723**	-2.580**	-1.489	-1.860	-2.967	-2.088	-1.764
$NegDCO_t$	-0.096	0.018	0.026	0.063	-0.019	0.087	-0.226	-0.118	-0.036	0.001
	-2.238**	0.287	0.388	0.622	-0.576	0.596	-1.287	-1.624	-0.630	0.009
$PosDCO_t$	-0.039	0.028	-0.253	0.094	-0.095	-0.049	-0.157	0.124	-0.148	-0.168
	-0.889	0.504	-2.187**	1.997**	-1.684*	-1.024	-0.653	0.963	-0.982	-0.856
$SIZE_t$	0.045	0.023	0.007	0.032	0.038	0.027	0.061	0.036	0.025	0.032
	4.444	1.764*	0.544	2.799**	2.654**	1.603	1.873*	2.907**	2.199	1.883
F- Stat	7.685***	1.413	1.923	4.218**	3.501**	1.760	1.554	3.263**	2.452*	1.896
R^2	1.22%	0.56%	1.32%	4.52%	3.62%	1.24%	0.90%	4.50%	3.17%	2.47%
Number of obs	1625	219	208	205	201	182	184	145	134	107

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

UE_CE_t	Unexpected core earnings measured as the difference between reported and predicted core earnings, where predicted values are estimated from the following equation: $CE_t = \alpha_0+\alpha_1 CE_{t-1}+\alpha_2 ACC_t+\alpha_3 ACC_{t-1} +\alpha_5 \Delta TA_{t,t-1} + \alpha_6 Neg\Delta TA_{t,t-1} +e_t$
$UE\_\Delta CE_{t+1}$	Unexpected change in core earnings is the difference between actual change in core earnings and predicted change in core earnings, where predicted values are estimated from the following equation: $\Delta CE_{t+1,t} = \beta_0+\beta_1\Delta CE_{t,t-1} +\beta_2 CE_t +\beta_3 ACC_{t+1}+ \beta_4 ACC_t + \beta_6 \Delta TA_{t+1,t} + \beta_7 Neg\Delta TA_{t,t-1} + \nu_t$
$NegDCO_t$	If losses from discontinued operations, and otherwise 0, scaled by Opening Total $Assets_{t,}$
$PosDCO_t$	If gains from discontinued operations, and otherwise 0, scaled by Opening Total $Assets_{t,}$
$SIZE_t$	Natural logarithm of Total $Assets_t$

Overall, findings in Table 24 provide evidence consistent with H1: managers engage in classification shifting using discontinued operations to increase core earnings. I further regress the models (5) and (6) for the DCO sample to examine whether managers use classification shifting to avoid reporting losses or/and earnings decreases.

Table 25 reports the regression results for Benchmarks 1 and 2, where discontinued operations are used to avoid reporting losses and/or earnings decreases. Panel A reports the regression results for model (5). The coefficients on $NegDCO_t$ are consistently positive and significant for benchmarks 1 and 2. The coefficient on the variable of interest, $M\&B_t$, interacted with $NegDCO_t$, is significant for benchmarks 1 (Υ_6=-0.192, p>0.*1*) and 2 (Υ_6=-0.243, p>0.001).

Panel B reports the regression results for model (6). The coefficient on the variable of interest, $M\&B_t$ interacted with $NegDCO_t$, is not significant for both benchmarks. These findings are not supportive of firms reporting discontinued operations engaging in classification shifting for benchmarks, avoiding losses and/or earnings decreases.

5.3.4 Material Discontinued Operations

Table 26 reports results of models (3) and (4) for samples with different levels of materiality in discontinued operations. Discontinued operations materiality is estimated in five and more percentages of discontinued operations of core earnings (DCO/CE). I employ this test in six samples that have different levels of materiality because I expect the coefficients on *NegDCO* will improve when the materiality increases. Panel A reports the regression results of model (3), the association between unexpected core earnings, and

losses and gains from discontinued operations. For model (3), the coefficient on $NegDCO_t$ is positive and significant for materiality levels. *PosDCO* is also negative and significant as expected. These findings suggest that classification shifting takes place when firms report material discontinued operations. The coefficients on *NegDCO* increase from 0.236 in 5% and more to 0.262 in 20% and more, however they decrease in the samples with larger materiality. This finding is contrary to the expectation that the coefficient on *NegDCO* improves when the materiality increases.

Panel B reports regression results of model (4), the association between unexpected change in core earnings, and losses and gains from discontinued operations. For model (4), the coefficients on $NegDCO_t$ are negative, but not significant for all levels of material samples, indicating there is no classification shifting among these samples.

Table 25 Benchmarks, Regressions of Unexpected Core Earnings and Unexpected Change in Core Earnings on Discontinued Operations, N=1625

Panel A: Dependent Variable = UE_CE_t				
Independent Variables	**Benchmark 1**		**Benchmark 2**	
	Avoid losses		**Avoid earnings decrease**	
	Coefficients	t-stat	Coefficients	t-stat
Intercept	-0.042	-0.825	-0.262	-5.620***
$NegDCO_t$	0.26	10.040***	0.326	11.363***
$PosDCO_t$	-0.03	-0.957	-0.02	-0.582
$SIZE_t$	0.005	0.693	0.029	4.952***
$M\&B_t$	0.075	4.776***	0.122	9.169***
$M\&B_t$*$NegDCO_t$	-0.192	-1.667*	-0.243	-4.868***
$M\&B_t$*$PosDCO_t$	0.039	0.715	0.027	0.556
F stat	31.974***		56.102***	
Adjusted R^2	10.27%		16.91%	
Panel B: Dependent Variable = $UE\_\Delta CE_{t+1,t}$				
Intercept	-0.438	-5.09	-0.35	-4.251***
$NegDCO_t$	-0.079	-1.804*	-0.077	-1.533
$PosDCO_t$	-0.03	-0.569	-0.032	-0.536
$SIZE_t$	0.059	5.184***	0.045	4.438***
$M\&B_t$	-0.069	-2.591**	-0.012	-0.527
$M\&B_t$*$NegDCO_t$	-0.24	-1.235	-0.059	-0.674
$M\&B_t$*$PosDCO_t$	-0.028	-0.307	-0.014	-0.161
F stat	5.109***		3.942***	
Adjusted R^2	1.50%		1.08%	

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

UE_CE_t Unexpected Core Earnings measured as the difference between reported and predicted core earnings, where predicted values are estimated from the following equation:

$$CE_t = \alpha_0+\alpha_1 CE_{t-1}+\alpha_2 ACC_t+\alpha_3 ACC_{t-1} +\alpha_5 \Delta TA_{t,\,t-1} + \alpha_6 Neg\Delta TA_{t,t-1} +e_t$$

$UE\_\Delta CE_{t+1}$ Unexpected Change in Core Earnings is the difference between actual change in core earnings and predicted change in core earnings, where predicted values are estimated from the following equation:

$$\Delta CE_{t+1,t} = \beta_0+\beta_1\Delta CE_{t,t-1} +\beta_2 CE_t +\beta_3 ACC_{t+1}+ \beta_4 ACC_t + \beta_6 \Delta TA_{t+1,\,t} + \beta_7 Neg\Delta TA_{t,t-1} + \nu_t$$

$NegDCO_t$ If losses from Discontinued Operations, and otherwise 0, are scaled by Opening Total $Assets_{t,}$

$PosDCO_t$ If gains from Discontinued Operations, and otherwise 0, are scaled by Opening Total $Assets_{t,}$

$SIZE_t$ Natural logarithm of Total $Assets_t$

$M\&B_t$ In benchmark 1, if the observation has core earnings greater than zero, and 0 otherwise

$M\&B_t$ In benchmark 2, if the observation has earnings changes greater than zero, and 0 otherwise

Table 26 Regressions of Unexpected Core Earnings and Unexpected Change in Core Earnings on Discontinued Operations, Material DCO Sample

Panel A: Dependent Variable = UE_CE_t

Independent Variable	Predicted sign	Material (DCO/CE)					
		≥5%	≥10%	≥20%	≥30%	≥40%	≥50%
(Constant)		-0.081	-0.032	0.063	0.05	0.057	0.066
		-1.572	-0.592	1.145	0.883	0.951	1.034
$NegDCO_t$	+	0.236	0.254	0.262	0.228	0.237	0.238
		7.972***	8.619***	9.619***	8.534***	8.681***	8.505***
$PosDCO_t$	-	-0.062	-0.071	-0.08	-0.077	-0.078	-0.082
		-3.245**	-3.806***	-4.748***	-4.861***	-4.841***	-5.051***
$SIZE_t$		0.015	0.009	-0.002	-0.001	-0.001	-0.002
		2.252**	1.335	-0.331	-0.108	-0.149	-0.218
F- Stat		34.506***	36.574***	40.165***	33.971***	34.869***	34.235***
R^2		7.42%	8.81%	11.43%	11.05%	12.34%	13.25%

Panel B: Dependent Variable = $UE\_\Delta CE_{t+1,t}$

Independent Variable	Material (DCO/CE)					
	5%	10%	20%	30%	40%	50%
(Constant)	-0.287	-0.291	-0.291	-0.217	-0.26	-0.2
	-2.987**	-3.037**	-2.420*	-1.843*	-2.028	-1.567
$NegDCO_t$	-0.046	-0.043	-0.043	-0.002	-0.038	-0.029
	-0.84	-1.311	-0.725	-0.04	-0.648	-0.514
$PosDCO_t$	-0.038	-0.017	-0.017	-0.015	-0.007	-0.02
	-1.069	-0.619	-0.463	-0.462	-0.206	-0.619
$SIZE_t$	0.037	0.038	0.038	0.029	0.034	0.026
	3.082**	3.095**	2.495**	1.948*	2.09	1.633
F- Stat	4.056**	3.695**	2.404*	1.231	1.624	1.231
R^2	0.73%	0.73%	0.46%	0.27%	0.26%	0.11%
Number of obs	1256	1105	911	797	723	654

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

5.3.5 Serial vs Non-Serial Discontinued Operations

Figure 5 shows the frequency of firms reporting discontinued operations in the test period. For example, 235 firms report discontinued operations twice during the period (the highest result), and one firm reports discontinued operations every year (11 times).

Figure 2 Frequency of Firms Reporting Discontinued Operations (2006-2016)

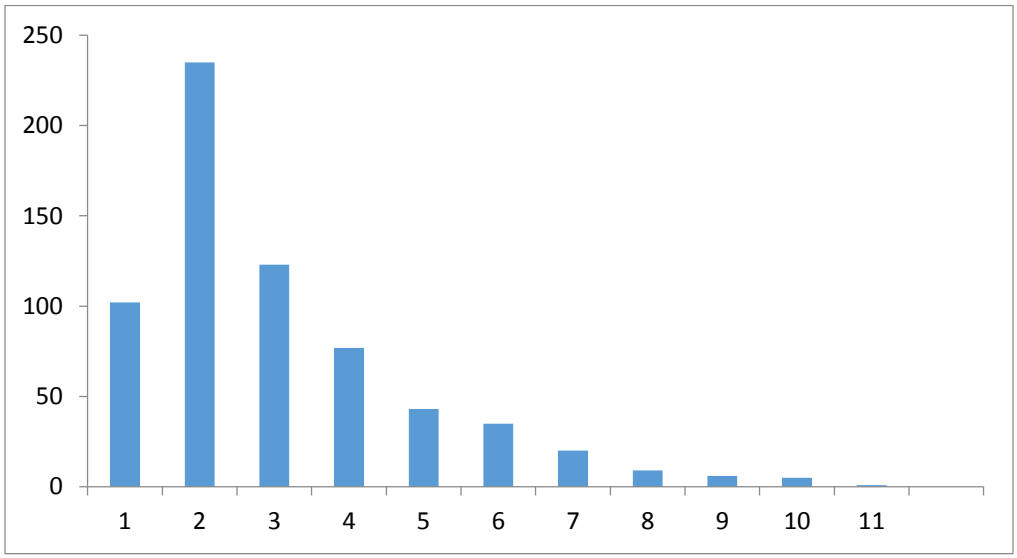


Table 27 reports regression results of models 3 (Panel A) and 4 (Panel B) for serial and the non-serial samples. For model (3), the coefficient on $NegDCO_t$ is positive and significant (δ_1 =0,182, p<0.001) for serial sample. However the coefficient of *NegDCO* is not significant for the non-serial sample. The coefficient on *PosDCO* is negative and significant for the serial sample. Panel B reports the regression results of model (4), the association between unexpected change in core earnings, and losses and gains from discontinued operations. For model (4), the coefficients on $NegDCO_t$ is not significant for both samples. This evidence does not support Barua et al.'s (2010) conclusion that serial and non-serial discontinued reporters use classification shifting.

Table 27 Serial vs Non-Serial Regressions of Unexpected Core Earnings and Unexpected Change in Core Earnings on Discontinued Operations

Panel A: Dependent Variable = UE_CE_t

Independent Variables		**Serial**		**Non-Serial**	
		Coefficients	t-stat	Coefficients	t-stat
Intercept		-0.184	-3.463***	-0.321	-1.814
$NegDCO_t$	(+)	0.182	5.236***	0.030	0.227
$PosDCO_t$	(-)	0.002	0.350	-0.008	-0.211
$SIZE_t$		0.026	3.913***	0.046	1.889
F stat		22.078***		1.345	
Adjusted R^2		5.50%		1.09%	

Panel B: Dependent Variable = $UE\_\Delta CE_{t+1,t}$

Independent Variables	Predicted sign	Coefficients	t-stat	Coefficients	t-stat
Intercept		-0.270	-4.951***	-0.257	-0.384
$NegDCO_t$		0.008	0.233	-0.193	-0.389
$PosDCO_t$		0.013	2.790**	0.02	0.137
$SIZE_t$		0.034	5.047***	0.033	0.364
F stat		12.093***		0.080	
Adjusted R^2		2.97%		-3.02%	
Number of obs		1088		95	

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

UE_CE_t Unexpected Core Earnings measured as the difference between reported and predicted core earnings, where predicted values are estimated from the following equation:

$$CE_t = \alpha_0+\alpha_1 CE_{t-1}+\alpha_2 ACC_t+\alpha_3 ACC_{t-1} +\alpha_5 \Delta TA_{t,t-1} + \alpha_6 Neg\Delta TA_{t,t-1} + e_t$$

$UE\_\Delta CE_{t+1}$ Unexpected Change in Core Earnings is the difference between actual change in core earnings and predicted change in core earnings, where predicted values are estimated from the following equation:

$$\Delta CE_{t+1,t} = \beta_0+\beta_1\Delta CE_{t,t-1} +\beta_2 CE_t +\beta_3 ACC_{t+1}+ \beta_4 ACC_t + \beta_6 \Delta TA_{t+1,t} + \beta_7 Neg\Delta TA_{t,t-1} + \nu_t$$

$NegDCO_t$ If losses from discontinued operations, and otherwise 0, are scaled by Opening Total $Assets_{t,}$

$PosDCO_t$ If gains from discontinued operations, and otherwise 0, are scaled by Opening Total $Assets_{t,}$

$SIZE_t$ Natural logarithm of Total $Assets_t$

5.3.6 Serial and Material Discontinued Operations

This sample contains observations with material (DCO/CE≥5%) discontinued operations in two or more consecutive years. Table 28, Panel A reports the regression results of model (3), and losses and gains from discontinued operations. For model (3), the coefficient on $NegDCO_t$ is positive and significant (δ_1 =0.210, p<0.001) as expected. The coefficients on *PosDCO* are negative and significant (δ_2 =0.200, p<0.001) as well. Panel B reports the regression results of model (4), unexpected change in core earnings, and losses and gains from discontinued operations. For model (4), the coefficient on $NegDCO_t$ is significant (λ_1 =0.059, p<0.1). These findings suggest that classification shifting takes place when firms report discontinued operations in consecutive years, and the amount of losses is significantly high.

As Table 28 shows there is a classification shifting for the sample with serial and material discontinued operations, the benchmark testings are further employed for this sample. Table 29 reports the regression results for Benchmarks 1 and 2, whether discontinued operations are used to avoid reporting losses and/or earnings decreases. Panel A reports the regression results for model (5). The coefficients on $NegDCO_t$ are consistently positive and significant for benchmarks 1 (∂_1=0.205, p>0.001) and 2 (∂_1=0.361, p>0.001). The coefficients on $PosDCO_t$ are consistently negative and significant for benchmarks 1 (∂_2=0.201, p>0.001) and 2 (∂_2=0.220, p>0.05) as well. The coefficients on the variable of interest, $M\&B_t$ interacted with $NegDCO_t$ are significant for benchmarks 1 (∂_4=-0.373, p>0.05) and 2 (∂_4=-0.262, p>0.001).

Panel B reports the regression results for model (6). The coefficients on the variable of interest, $M\&B_t$ interacted with $NegDCO_t$ are significant for benchmark 1 (Υ_4=-0.499, p>0.001) and 2 (Υ_4=-0.155, p>0.05). These findings support the evidence that firms reporting serial and material discontinued operations engage in classification shifting for both benchmarks 1 and 2.

Overall, the results suggest the firms reporting serial and material losses from discontinued operations tend to use classification shifting to avoid reporting losses and earnings decreases in the Australian context.

Table 28 Serial & Material Regressions of Unexpected Core Earnings and Unexpected Change in Core Earnings on Discontinued Operations

Panel A: Dependent Variable = UE_CE_t

Independent Variables	Predicted sign	**Serial & Material**	
		Coefficients	t-stat
Intercept		-0.070	-1.202
$NegDCO_t$	(+)	0.210	6.252***
$PosDCO_t$	(-)	-0.200	-3.883***
$SIZE_t$		0.013	1.820*
F stat		24.732***	
Adjusted R^2		7.78%	

Panel B: Dependent Variable = $UE\_\Delta CE_{t+1,t}$

Independent Variables	Predicted sign	Coefficients	t-stat
Intercept		-0.234	-3.795***
$NegDCO_t$		0.059	1.650*
$PosDCO_t$		0.048	0.869
$SIZE_t$		0.031	4.056***
F stat		10.160***	
Adjusted R^2		3.15%	
Number of obs		845	

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively.

UE_CE_t Unexpected core earnings measured as the difference between reported and predicted core earnings, where predicted values are estimated from the following equation:

$$CE_t = \alpha_0+\alpha_1 CE_{t-1}+\alpha_2 ACC_t+\alpha_3 ACC_{t-1} +\alpha_5 \Delta TA_{t,t-1} + \alpha_6 Neg\Delta TA_{t,t-1} + e_t$$

$UE\_\Delta CE_{t+1}$ Unexpected change in core earnings is the difference between actual change in core earnings and predicted change in core earnings, where predicted values are estimated from the following equation:

$$\Delta CE_{t+1,t} = \beta_0+\beta_1\Delta CE_{t,t-1} +\beta_2 CE_t +\beta_3 ACC_{t+1}+ \beta_4 ACC_t + \beta_6 \Delta TA_{t+1,t} + \beta_7 Neg\Delta TA_{t,t-1} + \nu_t$$

$NegDCO_t$ If losses from discontinued operations, and otherwise 0, are scaled by Opening Total $Assets_t$,

$PosDCO_t$ If gains from discontinued operations, and otherwise 0, are scaled by Opening Total $Assets_t$

$SIZE_t$ Natural logarithm of Total $Assets_t$

Table 29 Serial and Material Benchmark Regressions of Unexpected Core Earnings and Unexpected Change in Core Earnings on Discontinued Operations

Panel A: Dependent Variable = UE_CE_t

Independent Variables	Predicted sign	Serial & Material			
		Benchmark 1		Benchmark 2	
		Avoid losses		Avoid earnings decreases	
		Coefficients	t-stat	Coefficients	t-stat
Intercept		0.000	-0.006	-0.185	-3.296***
$NegDCO_t$	(+)	0.205	6.020***	0.361	7.919***
$PosDCO_t$	(-)	-0.201	-3.929***	-0.220	-2.978**
M&B		0.058	3.187***	0.107	7.114***
M&B*NegDCO		-0.373	-3.033**	-0.262	-4.561***
M&B*PosDCO		0.854	2.850**	0.061	0.642
$SIZE_t$		0.000	0.004	0.021	3.080**
F stat		20.881***		37.354***	
Adjusted R^2		12.38%		20.54%	

Panel B: Dependent Variable = $UE\_\Delta CE_{t+1,t}$

Independent Variables	Predicted sign	Coefficients	t-stat	Coefficients	t-stat
Intercept		-0.280	-4.312	-0.235	-3.675***
$NegDCO_t$		0.100	2.709**	0.148	2.836**
$PosDCO_t$		0.037	0.665	0.085	1.000
M&B		-0.054	-2.733**	-0.002	-0.140
M&B*NegDCO		-0.499	-3.749***	-0.155	-2.367**
M&B*PosDCO		-0.005	-0.015	-0.063	-0.580
$SIZE_t$		0.039	4.670***	0.031	4.059***
F stat		8.121***		6.309***	
Adjusted R^2		4.82%		3.64%	
Number of obs		845		845	

*,**,*** Indicate at the 10, 5, and 1 percent levels, respectively. DCO are scaled by opening total assets.

UE_CE_t Unexpected core earnings measured as the difference between reported and predicted core earnings, where predicted values are estimated from the following equation:

$$CE_t = \alpha_0+\alpha_1 CE_{t-1}+\alpha_2 ACC_t+\alpha_3 ACC_{t-1} +\alpha_5 \Delta TA_{t,\,t-1} + \alpha_6 Neg\Delta TA_{t,t-1} +e_t$$

$UE\_\Delta CE_{t+1}$ Unexpected change in core earnings is the difference between actual change in core earnings and predicted change in core earnings, where predicted values are estimated from the following equation:

$$\Delta CE_{t+1,t} = \beta_0+\beta_1\Delta CE_{t,t-1} +\beta_2 CE_t +\beta_3 ACC_{t+1}+ \beta_4 ACC_t + \beta_6 \Delta TA_{t+1,\,t} + \beta_7 Neg\Delta TA_{t,t-1} + \nu_t$$

$NegDCO_t$ If losses from discontinued operations, and otherwise 0, are scaled by Opening Total $Assets_{t,}$

$PosDCO_t$ If gains from discontinued operations, and otherwise 0, are scaled by Opening Total $Assets_{t,.}$

$SIZE_t$ Natural logarithm of Total $Assets_t$

$M\&B_t$ In benchmark 1, if the observation has core earnings greater than zero, and 0 otherwise

$M\&B_t$ In benchmark 2, if the observation has earnings changes greater than zero, and 0 otherwise

5.4 Chapter Summary

This chapter reviews the literature of classification shifting for non-recurring items including discontinued operations, develops hypotheses and research designs, and demonstrates results for classification shifting of discontinued operations under IFRS.

The chapter provides an overview of the existing literature relating to classification shifting of non-recurring items. The overview starts with brief information on earnings management and proceeds to discuss further the literature of classification shifting. Previous studies show that managers opportunistically shift core expenses to non-recurring items to increase core earnings (McVay, 2006; Barua et al., 2010; Fan et al., 2010). Current findings also support the notion that managers engage in classification shifting to meet or beat three benchmarks: zero earnings, prior year's earnings, and analysts' forecasts (McVay, 2006; Barua et al., 2010; Fan et al., 2010).

With respect to the research design, the McVay (2006) model is applied to examine classification shifting for discontinued operations. In the classification shifting analysis, I include the variable of firm size because the sample used in this thesis contains different sized companies. The results show that unexpected core earnings and unexpected changes in core earnings are significantly associated with losses from discontinued operations for firms that report discontinued operations. Findings from benchmarks tests do not generally support the hypothesis that Australian firms engage in classification shifting using discontinued operations to avoid losses and earnings decreases. However, in the additional test for firms reporting a serial and material amount of discontinued operations, results are consistent with the hypothesis that discontinued operations are used to manipulate core earnings to avoid reporting losses and earnings decreases. Findings from benchmark testing support the view that classification shifting takes place when firms report discontinued operations frequently and the amount of losses is significantly high.

The next chapter concludes the thesis.

6. CONCLUSION

6.1 Summary of the Thesis

This thesis investigates the usefulness of disaggregating discontinued operations in the statement of comprehensive income under IFRS-5 and provides empirical evidence for the predictive ability and classification shifting of discontinued operations.

IFRS-5 requires the separate reporting of discontinued operations in the statement of comprehensive income. The requirement is based on the (untested) assertion that cash flows from discontinued operations are different from continuing flows. It is observed that there is a need to examine whether it is useful to report separately the line item of discontinued operations in the statement of comprehensive income under IFRS. Therefore, this thesis examines the usefulness of disaggregating discontinued operations in two important ways: predictive ability and classification shifting.

The literature of discontinued operations is reviewed in Chapter 3. There have been few studies that relate to discontinued operations. Studies investigate the effects of acquisitions and corporate focus on decisions relating to discontinued operations (Lord & Saito, 2017), predictive ability (Curtis et al., 2014) and classification shifting of discontinued operations (Barua et al., 2010). All these studies are conducted on US data that adopted US GAAP. This thesis samples Australian listed companies obtained from Thomson Reuters Eikon, spanning 2006-2016.

In Chapter 4, the literature review for predictive ability, research design and the results of predictive ability of discontinued operations are discussed. With regard to the predictive ability of non-recurring items, existing research shows mixed results. Some studies (Cameron & Stephens, 1991; Fairfield et al., 1996; Ohlson,1999; Bradshaw & Sloan, 2002) demonstrate that non-recurring items can be ignored to predict a company's profitability because they decrease predictive ability. In contrast, others studies (Burgstahler et al., 2002; Fairfield et al., 2009) find that negative special items are associated with future profits; non-

recurring items receive more attention from financial information users and have straightforward implications for expected future earnings.

The results show that discontinued operations are useful to predict a company's future performance. In particular, losses from discontinued operations are strongly associated with one-year-ahead net income for the DCO sample.

In Chapter 5, the literature review for classification shifting of non-recurring items including discontinued operations, research design, and results of classification shifting for discontinued operations, are discussed. Past research has shown that managers opportunistically transfer core expenses to non-recurring items to increase core earnings. Although extensive research has been carried out on different non-recurring items, no study examines classification shifting of discontinued operations under IFRS. The results show that managers use discontinued operations to manipulate earnings. Unexpected core earnings are strongly associated with losses from discontinued operations. There is also a significant association between unexpected change in core earnings and discontinued operations-driven firms with losses from discontinued operations. I interpret these results as evidence that firms engage in classification shifting using discontinued operations under IFRS. Findings suggest that classification shifting takes place when firms report discontinued operations frequently and the amount of losses is significantly high. For the benchmark tests, results reveal that managers manipulate earnings to avoid reporting losses and earnings decreases under IFRS.

6.2 Policy Implications for Standard Setters

The findings of this thesis have implications for standard setters. The results of the study indicate that, in general, disaggregating net income into continuing and discontinued operations is useful to predict a company's future profitability. It supports keeping the current separate line of reporting of discontinued operations in the statement of comprehensive income.

However, another important practical implication is that losses from discontinued operations are opportunistically used to manipulate core earnings. How to mitigate classification shifting might be a concern for IASB. There have been some studies that could help mitigate classification shifting by improving institutional control of a company's auditors (Naman & Neerav, 2016), financial analysts (Behn, Gotti, Herrmann, & Kang, 2013), and internal audit committees (Zalata & Roberts, 2016).

6.3 Future Research Opportunities

This thesis highlights several prospective areas for future research. First, the IASB may want to assess the value relevance of discontinued operations. How well discontinued operations reflect equity investors can be extended to this research, since the relevance is one of the qualitative characteristics of the IFRS conceptual framework.

Second, research relating to discontinued operations is mostly conducted in developed markets; there is not much literature that looks at the usefulness of separating discontinued operations in developing countries. Existing literature identifies various institutional differences in developed and underdeveloped countries. Taking a developing country and comparing it with a developed market, such as Australia, might lead to contrasting results.

Third, future study on whether managers engage classification shifting using discontinued operations to meet and beat analysts' forecast is recommended under IFRS. A similar study was conducted for the US. A sample that adopted IFRS could be examined, which would lead to better insights on classification shifting of discontinued operations to meet and beat analysts' forecasts.

Fourth, an interesting area that could be an extension of this study would be a review of ways to mitigate classification shifting under IFRS. Findings would be helpful to consider the issue overall, and to take steps to make the required standard improvements for IASB.

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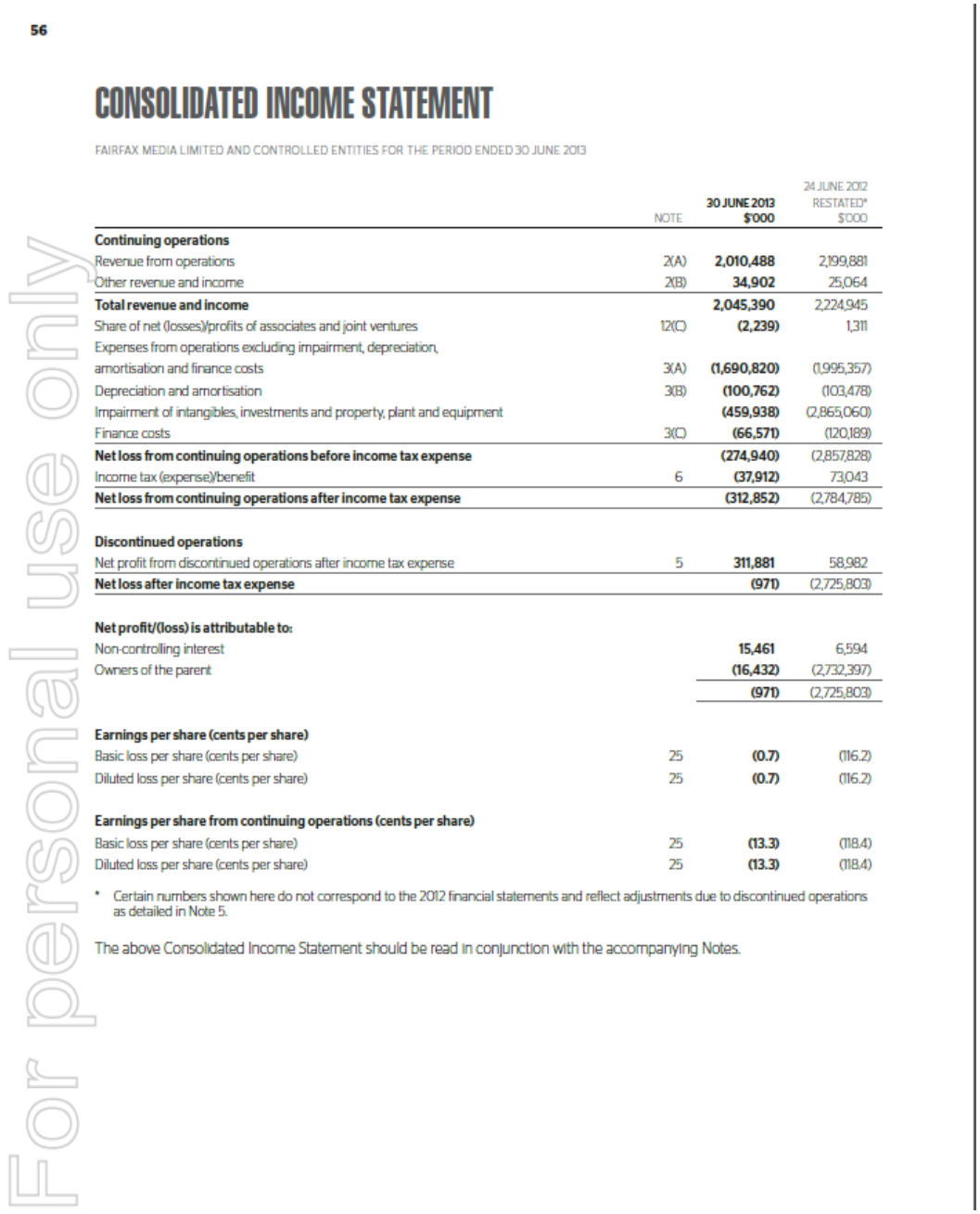
APPENDICES

Appendix 1 Example of Reporting Discontinued Operations as Required by IFRS-5[24]



56

CONSOLIDATED INCOME STATEMENT

FAIRFAX MEDIA LIMITED AND CONTROLLED ENTITIES FOR THE PERIOD ENDED 30 JUNE 2013

	NOTE	30 JUNE 2013 $'000	24 JUNE 2012 RESTATED* $'000
Continuing operations			
Revenue from operations	2(A)	**2,010,488**	2,199,881
Other revenue and income	2(B)	**34,902**	25,064
Total revenue and income		**2,045,390**	2,224,945
Share of net (losses)/profits of associates and joint ventures	12(C)	**(2,239)**	1,311
Expenses from operations excluding impairment, depreciation, amortisation and finance costs	3(A)	**(1,690,820)**	(1,995,357)
Depreciation and amortisation	3(B)	**(100,762)**	(103,478)
Impairment of intangibles, investments and property, plant and equipment		**(459,938)**	(2,865,060)
Finance costs	3(C)	**(66,571)**	(120,189)
Net loss from continuing operations before income tax expense		**(274,940)**	(2,857,828)
Income tax (expense)/benefit	6	**(37,912)**	73,043
Net loss from continuing operations after income tax expense		**(312,852)**	(2,784,785)
Discontinued operations			
Net profit from discontinued operations after income tax expense	5	**311,881**	58,982
Net loss after income tax expense		**(971)**	(2,725,803)
Net profit/(loss) is attributable to:			
Non-controlling interest		**15,461**	6,594
Owners of the parent		**(16,432)**	(2,732,397)
		(971)	(2,725,803)
Earnings per share (cents per share)			
Basic loss per share (cents per share)	25	**(0.7)**	(116.2)
Diluted loss per share (cents per share)	25	**(0.7)**	(116.2)
Earnings per share from continuing operations (cents per share)			
Basic loss per share (cents per share)	25	**(13.3)**	(118.4)
Diluted loss per share (cents per share)	25	**(13.3)**	(118.4)

* Certain numbers shown here do not correspond to the 2012 financial statements and reflect adjustments due to discontinued operations as detailed in Note 5.

The above Consolidated Income Statement should be read in conjunction with the accompanying Notes.

[24] An extract from one of the Australian listed companies.

Appendix 2 Display of Discontinued Operations Reporting in the Notes[25]

NOTES TO THE FINANCIAL STATEMENTS

FAIRFAX MEDIA LIMITED AND CONTROLLED ENTITIES FOR THE PERIOD ENDED 30 JUNE 2013

5. DISCONTINUED OPERATIONS

On 21 December 2012, the Group disposed of its remaining 51% interest in Trade Me Group Ltd for proceeds of A$605.5 million net of transaction fees.

The Trade Me business had its own operating segment within the segment reporting disclosures (refer Note 37).

As at 30 June 2013, the Trade Me business has been classified as a discontinued operation. The financial information presented below is for the period ended 21 December 2012 and the comparative period is for the year ended 24 June 2012.

	2013 $'000	2012 $'000
Total revenue and income	**60,871**	114,243
Share of net profits of associates and joint ventures	**–**	435
Expenses	**(21,229)**	(34,694)
Net profit before income tax expense	**39,642**	79,984
Income tax expense	**(11,205)**	(21,002)
Net profit after income tax expense	**28,437**	58,982
Gain on sale of discontinued operations *	**283,444**	–
Income tax expense	**–**	–
Net profit from discontinued operations after income tax expense	**311,881**	58,982

* The gain on sale is associated with the disposal of the Group's 51% interest in Trade Me Group Ltd. Previous disposals of the Group's interest in this entity have resulted in a gain on sale of $182.8 million recorded in equity as an acquisition reserve while the Group still retained control.

	2013 ¢ PER SHARE	2012 ¢ PER SHARE
Earnings per share		
Basic earnings per share from discontinued operations	**13.3**	2.5
Diluted earnings per share from discontinued operations	**13.3**	2.5

	2013 $'000	2012 $'000
Cash flows of discontinued operations		
The net cash flows incurred by discontinued operations are as follows:		
Operating	**27,010**	56,489
Investing	**(4,020)**	(21,275)
Financing	**(26,894)**	(9,393)
Net cash (outflow)/inflow	**(3,904)**	25,821

[25] An extract from one of the Australian listed companies.

Appendix 3 Display of Discontinued Operations Reporting in the Notes (columnar format)[26]

Notes to the Consolidated Financial Statements
For the Year ended 30 September 2013

Note 37. Discontinued Operations

Financial period 30 September 2013

The Group's investment in the Futuris Automotive segment was disposed of during the period. Additionally the Group's investment in Australian Fine China and Agricultural Land Trust were classified as held for sale.

As required by AASB 5 Non-current Assets Held for Sale and Discontinued Operations the 2012 comparative discontinued operations disclosed below have been re-presented to show the effects of this classification.

Financial period 30 September 2012

Operations within the Group's Forestry division, and the Group's investment in Seed Technology and Marketing Pty Ltd ('Seedmark'), which forms part of the Rural Services segment, were classified as discontinued operations, or were disposed of during the period ended 30 September 2012 and reported as discontinued operations.

The Group's Forestry division continues to be classified as discontinued operations in the current financial year.

	Cont 2013 $000	**Disc 2013 $000**	**Total 2013 $000**	Cont 2012 $000	Disc 2012 $000	Total 2012 $000
Sales revenue	**1,657,112**	**305,542**	**1,962,654**	1,813,205	359,353	2,172,558
Cost of sales	**(1,332,713)**	**(269,542)**	**(1,602,255)**	(1,426,921)	(317,360)	(1,744,281)
Other revenues	**2,415**	**13,566**	**15,981**	13,929	20,692	34,621
Other expenses	**(568,777)**	**(238,111)**	**(806,888)**	(457,593)	(121,946)	(579,539)
Share of profit of associates and joint ventures	**11,475**	**(3,105)**	**8,370**	14,097	(6,325)	7,772
Profit/(loss) on sale of non current assets	**25,939**	**(40,278)**	**(14,339)**	179	26,956	27,135
Profit/(loss) before net borrowing costs and tax expense	**(204,549)**	**(231,928)**	**(436,477)**	(43,104)	(38,630)	(81,734)
Interest revenue	**8,792**	**1,471**	**10,263**	30,753	1,300	32,053
Finance costs	**(31,032)**	**(4,808)**	**(35,840)**	(38,626)	(1,916)	(40,542)
Profit/(loss) before tax expense	**(226,789)**	**(235,265)**	**(462,054)**	(50,977)	(39,246)	(90,223)
Income tax benefit/(expense)	**(65,966)**	**26,150**	**(39,816)**	38,313	(5,463)	32,850
Net profit/(loss) for year	**(292,755)**	**(209,115)**	**(501,870)**	(12,664)	(44,709)	(57,373)
Net profit/(loss) attributable to non-controlling interest	**3,057**	**328**	**3,385**	3,194	33	3,227
Net profit/(loss) attributable to members of the parent entity	**(295,812)**	**(209,443)**	**(505,255)**	(15,858)	(44,742)	(60,600)
Revenue and expenses						
Sales revenue:						
Sale of goods and biological assets	**1,458,292**	**304,441**	**1,762,733**	1,593,518	356,398	1,949,916
Commission and other selling charges	**168,138**	**856**	**168,994**	190,540	1,658	192,198
Other sales related income	**30,682**	**245**	**30,927**	29,147	1,297	30,444
	1,657,112	**305,542**	**1,962,654**	1,813,205	359,353	2,172,558
Other expenses:						
Distribution expenses	**260,856**	**23**	**260,879**	263,138	32	263,170
Marketing expenses	**7,253**	**358**	**7,611**	9,359	475	9,834
Occupancy expenses	**31,610**	**3,108**	**34,718**	33,759	3,583	37,342
Administrative expenses	**78,357**	**49,560**	**127,917**	97,567	53,554	151,121
Forestry fair value adjustments	**(7,422)**	**(6,664)**	**(14,086)**	36,025	44,050	80,075
Write down of assets to be divested or discontinued	**-**	**189,798**	**189,798**	-	4,198	4,198
Impairment of assets retained	**137,302**	**-**	**137,302**	18,634	-	18,634
Restructuring, redundancy and other writeoffs	**57,861**	**1,741**	**59,602**	(889)	14,125	13,236
Change in fair value of financial and other assets	**2,960**	**187**	**3,147**	-	1,929	1,929
	568,777	**238,111**	**806,888**	457,593	121,946	579,539
Profit/(loss) on sale of non current assets						
Non current assets held for sale	**-**	**(2,594)**	**(2,594)**	-	16,620	16,620
Equity accounted investments	**25,988**	**-**	**25,988**	-	(293)	(293)
Property, plant and equipment	**(49)**	**-**	**(49)**	179	-	179
Intangibles	**-**	**224**	**224**	-	-	-
Controlled entities	**-**	**(37,908)**	**(37,908)**	-	10,629	10,629
	25,939	**(40,278)**	**(14,339)**	179	26,956	27,135

113

[26] An extract from one of the Australian listed companies.

Appendix 4 Review of Empirical Studies on Discontinued Operations

Studies	**Sample**	**Dependent Variable**	**Independent Variable**	**Methodology**	**Findings**
Lord and Saito (2017)	123415 with 15895 observations reporting DCO 1976-2012 from Compustat data	Revenue, Leverage and Tobin Q in three years prior	Revenue, Leverage and Tobin Q in three years after	Univariate analysis Multinomial Logistic Regression	After the change in reporting requirement of SFAS 2002, the portion of firms discontinuing operations more than doubles in almost one third of industries (1), the firms that divest are unusually widely diversified, have high financial leverage, and have low value of Tobin's Q (2), after a discontinuation, the performance of a company improves (3).
Curtis, McVay and Wolfe (2014)	201207 with 39469 observations reporting DCO 1995-2000 and 2002-2007 from Compustat data	Continuing Income one year ahead	Continuing Income lagged and Discontinued operations	Regression Fairfield et al. (1996)	More firms report discontinued operations and an increase in the persistence of continuing income under SFAS 144. Overall, their result supports the broader scope of discontinued operations (SFAS 144).
Barau, Lin and Sbaraglia (2010)	79643 with 6262 observations reporting DCO 1988-2006 from Compustat data	Unexpected Core Earnings $(UE\_CE)_t$ Unexpected Change in Core Earnings $(UE\_\Delta CE)_{t+1}$	Discontinued operations and other variables	Extended McVay (2006) model	Firms shift operating expenses to income, decreasing DCO to increase core earnings. Managers use classification shifting to meet or beat analysts' forecasts.

Appendix 5 Review of Empirical Studies on Predictive Ability in Non-recurring Items

Studies	**Sample**	**Dependent Variable**	**Independent Variable**	**Methodology**	**Findings**
Fairfield, Sweeney and Yohn (1996)	15636 firm-year observations 1981-90 period from Compustat	ROE_t	Component of $earnings_{t-1}$	Cross sectional time series regression models	The classification scheme prescribed by the accounting profession does increase the predictive content of reported earnings. However, extraordinary and discontinued operations can be ignored in forecasting future profitability.
Dechow and Ge (2006)	63875 firm-year observations, 1988-2002 period from Compustat and CRSP	$Earnings_t$, $Cash\ flows_t$	$Earnings_{t-1}$ $Cash\ flows_{t-1}$	Least Square Regression	Low accrual firms with negative special items have higher returns on assets and higher market returns in future years.
Fairfield, Kitching and Tang (2009)	24262 firm-year observations, 1984-2003 period from Compustat	Profit $margin_{t+1}$	Core earnings, Special positive and negative $special\ items_t$	Least Square Regression	The association between past special items and future profit margins differs markedly between firms with low or high profitability. For high profitability firms, negative special items are associated with lower future profit margins.
Cready, Lopez, and Sisneros (2010)	112721 firm-quarter observations, 1992-2003 period from Compustat and CRSP	Quarterly income before extraordinary $items_{t+1}$	Quarterly income before extraordinary $items_{t+1}$ and $Special\ items_t$	Least Square Regression	As the frequency of reporting negative special items increases, the persistence of these items significantly increases with respect to future earnings.
Jones and Smith (2011)	14671 firms 1976-2005 period from Compustat and CRSP	Net income and cash flow	Special items and Other comprehensive income	Least Square Regression	Special items and other comprehensive income are value relevant. Both negative and positive special items have strong predictive value for forecasting both future net income and future cash flows.

Appendix 6 Review Studies on Earnings Management

Studies	**Content**	**Findings**
Healy and Wahlen (1999)	Review of Earnings Management	Review of academic evidence on earnings management and its implication for accounting setters and regulators.
Degeorge, Patal and Zeckhauser (1999)	Three thresholds of Earnings Management	Identified three thresholds that help drive earnings management: (1) report positive profit, (2) sustain recent performance and (3) meet analysts' expectations.
Burgstahler and Dichev (1997)	Earnings Management	Unusually high frequencies of small increases in earnings and positive income; unusually low frequencies of small decreases in earnings and losses in distribution in the US.
Holland and Ramsay (2003)	Earnings Management	Unusually high frequencies of small increases in earnings and positive income; unusually low frequencies of small decreases in earnings and losses in distribution in Australia.
Bartov, Givoly and Hayn (2002)	Rewards to Earnings Management	Firms that meet or beat current analysts' earnings expectations (MBE) enjoy a higher return over the quarter than firms with similar quarterly earnings forecast errors that fail to meet these expectations. Further, such a premium to MBE, although somewhat smaller, exists in the cases where MBE is likely to have been achieved through earnings or expectations management.
Jiang (2008)		Firms beating three earnings thresholds enjoy higher rating upgrades and a smaller initial bond yield spread.

Appendix 7 Review of Empirical Studies on Classification Shifting

Studies	**Sample**	**Dependent Variable**	**Independent Variable**	**Methodology**	**Findings**
Barney, Ronen and Sadan (1976)	1951-1970 firms from four industries: paper, chemicals, rubber and airlines.	Extraordinary items	Observed smoothed variables (operating income)	Lease Square Regression	Managers use extraordinary items to manipulate net income.
McVay (2006)	76901 firm observations, 1988-2003 from Compustat data	Unexpected Core Earnings (UE_CE) Unexpected Change in Core Earnings (UE_ΔCE)	Special Items (SI)	Core earnings expectation model and Least Squares Regression	Managers opportunistically shift expenses from core expenses to special items.
Barau, Lin and Sbaraglia (2010)	79643 with 6262 observations, reporting DCO 1988-2006 from Compustat data	Unexpected Core Earnings $(UE\_CE)_t$ Unexpected Change in Core Earnings $(UE\_\Delta CE)_{t+1}$	Discontinued operations and other variables	Extended McVay (2006) model	Firms shift operating expenses to income decreasing DCO to increase core earnings. Managers use classification shifting to meet or beat analysts' forecasts.
Fan, Barau, Cready and Thomas (2010)	67980 firm quarters 1988-2007 from Compustat Quarterly File	Unexpected Core Earnings (UE_CE) Unexpected Change in Core Earnings (UE_ΔCE)	Special Items (SI)	Extended McVay (2006) model	Classification shifting is more likely in the fourth quarter than in interim quarters.
Christensen, Merkley, Tucker and Venkataraman (2011)	2003-2007 from Compustat and CRSP	Core Earnings	Special items (SI)	Lease Square Regression	Managers play an active role in influencing the composition of street earnings through earnings guidance.
Haw, Ho and Li (2011)	3992 firm-year obervations, 2001-2004 period from eight East Asian countries	Unexpected Core Earnings (UE_CE) Unexpected Change in Core Earnings (UE_ΔCE)	Special Items (SI)	McVay (2006) model	Expense misclassification is a pervasive and economically significant phenomenon in East Asia.

Shirato and Nagata (2012)	13230 firm-year observations, 2001-2011 period from Tokyo Stock Exchange.	Unexpected Core Earnings (UE_CE) Unexpected Change in Core Earnings (UE_ΔCE)	Special Items (SI)	McVay (2006) model	There is a strong tendency for managers to shift expenses (gains) downward (upward) to increase core earnings. This tendency is more pervasive when it enables a firm to meet earnings forecasts.
Abernathy, Bever and Rapley (2014)	33619 firm-year observations, 1988-2011 period from Compustat, CRSP and IBES.	Classification shifting	Real activity and accrual earnings management	Logistic Regression Analysis	Managers are more likely to use classification shifting when real earnings management is constrained by poor financial conditions, high levels of institutional ownership, and low industry market share.
Noh, Moon, Guiral and Esteban (2014)	1230 observations, 2011 from Korean Information Services	Unexpected Core Earnings (UE_CE) Unexpected Change in Core Earnings (UE_ΔCE)	Special Items (SI) Other operating income	Extended McKay (2006) regression model	Companies engaged in classification shifting use other operating income in the IFRS adoption period, and a performance-driven effect is more prevalent with respect to special expense items.
Alfonso, Cheng and Pan (2015)	94221 firm-year observations, 1988-2010 from Compustat and CRSP	Core Earnings$_{t+1}$	Core Earnings$_{t}$	McVay (2006) Mishkin test and the zero-investment return method	Market's expectation of core earnings' persistence is higher than the actual reported earnings persistence of firms that have shifted their core earnings.

VITA

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