DISCRETIONARY ACCRUALS AND THE PREDICTIVE ABILITY OF EARNINGS IN THE FORECAST OF FUTURE CASH FLOWS: EVIDENCE FROM AUSTRALIA

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Abstract

We examine whether discretionary and non-discretionary accruals improve the predictive ability of earnings for forecasting future cash flows in an Australian context. Using both within-sample and out-of-sample forecasting tests, we demonstrate that discretionary accruals improve the predictive abilty of earnings in the forecast of future cash flows. Further, discretionary and non-discretionary accruals and direct method cash flow components together are more useful than (i) aggregate earnings, (ii) aggregate cash flow from operations and total accruals, and (iii) aggregate cash flow from operations, discretionary accruals and nondiscretionary accruals.

Keywords: Discretionary Accruals, Nondiscretionary Accruals, Cash Flow, Earnings, Future Cash Flows, Australia

JEL Classification: M41

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1. Introduction

We investigate whether decomposing accruals into discretionary and non-discretionary components improves the predictive ability of earnings for forecasting future cash flows. There are two perspectives in positive accounting theory about the role of discretionary accruals in the usefulness of earnings: signaling and opportunism. According to the signaling hypothesis, discretionary accruals can improve the information content of earnings by allowing managers to signal their private information about future cash flows. However, according to the opportunism hypothesis, discretionary accruals can be used opportunistically, and thus can distort the information in earnings (e.g., Watts and Zimmerman, 1986). There is substantial empirical evidence that managers may manipulate earnings due to various incentives, such as earnings-based management compensation schemes (e.g., Healy, 1985; Guidry *et al.*, 1999) or executive stock options (e.g., Bartov and Mohanram, 2004; Bergstresser and Philippon, 2006). However, there is relatively scarce evidence (e.g., Subramanayam, 1996; Xie, 2001; Tucker and Zarowin, 2006) on whether *on average* managerial discretion is used to distort earnings' informativeness or to convey useful information to investors. In addition, in evaluating the relative usefulness of discretionary and non-discretionary accruals, most of the previous studies have used stock returns as a surrogate of future cash flows, rather than using future cash flows directly.

The forecasting of future cash flows is fundamental to a firm's valuation and its investment analysis (e.g., Krishnan and Largay, 2000); as well, accounting standard-setters argue that forecasting future cash flows is one of the prime objectives of financial reporting [1]. Thus, any investigation to identify models that improve forecasting of future cash flows should be of interest to preparers, users and regulators of financial reporting. Further, Sloan (1996) and Xie (2001), *inter alia*, show that the differential persistence of the accrual and cash flow components of earnings is not accurately priced by the market. This casts doubt on the application of share prices in assessing the relevance of cash flow and accruals.

Subramanyam (1996) provides the first evidence on this issue by investigating the association of cash flow from operations, discretionary accruals, and nondiscretionary accruals (as earnings components) with future cash flows. He employs the Jones (1991) model to separate total accruals into discretionary and nondiscretionary accruals. Subramanyam assumes that if discretionary accruals can predict future cash flows, managers use discretionary accruals to signal their private information rather than using them opportunistically. His results show that both discretionary and nondiscretionary accruals incrementally enhance the predictive ability of earnings for future cash flows over cash flow from operations. Subramanyam's results, however, are not conclusive about the relative importance of discretionary and non-discretionary accruals in predicting future cash flows for three reasons.

First, the reliability of Subramanyam's (1996) results has been questioned by Bernard and Skinner (1996), and Hribar and Collins (2002). Bernard and Skinner (1996) argue that the mismeasurement of discretionary accruals can be an alternative explanation for Subramanyam's (1996) findings. In particular, the Jones (1991) model employed by Subramanyam (1996) sysmatically misclassifies nondiscretionary accruals into discretionary accruals and thereby, may falsely indicate that discretionary accruals are value relevant. Furthermore, Hribar and Collins (2002) find that total accruals estimated by the balance sheet approach, as in Subramanyam (1996), are subject to substantial measurement errors; discretionary and nondiscretionary accruals embed some (or all) such errors, as opposed to the cash flow approach. Hribar and Collins (2002) further show that the coefficients on discretionary and nondiscretionary accruals reported in Subramanyam (1996) are affected by errors in total accruals and are therefore biased.

Second, Subramanyam's results are based on a model in which earnings are disaggregated into aggregate cash flow from operations, discretionary accruals, and nondiscretionay accruals. However, it is unclear whether the results would hold if the direct method cash flow components were incorporated instead of aggregate cash flow from operations in his cash flow prediction model. In particluar, cash flow components provide different information in predicting future cash flows (e.g., Krishnan and Largay, 2000; Cheng and Hollie, 2008; Orpurt and Zang, 2009); hence, constraining coefficients on cash flow from operations to be equal, as per Subramanyam (1996), may bias the explanatory power of the model as well as the estimated coefficients on discretionary and nondiscretionary accruals. Finally, to the extent the level of managers' discretions and constraints for earnings recognition differs across countries (Bartov *et al*., 2001), the generalisability of Subramanyam's findings (premised on the US setting) to other settings is questionable.

In light of the above discussion, this study addresses the following research question: do discretionary and nondiscretionary accruals, on average, enhance the predictive ability of earnings to forecast future cash flows in an Australian context? Australian firms provide a unique empirical context as they have been reporting *actual* cash flow components since 1992 [2]. This is significant because prior studies (e.g., Krishnan and Largay, 2000; Orpurt and Zang, 2009) provide evidence of material measurement errors when estimating cash flow components. More importantly, Orpurt and Zang (2009) find that the association of *estimated* CFO components and future cash flows are affected by the degree of these measurement errors. Therefore, this study avoids aggregagation bias, estimation errors, and possible model misspecification, as suffered by most previous studies in this area, in particular Subramanyam (1996). In addition, during the period of this study, Australian companies were allowed to re-evaluate non-current accruals, capitalise research and development expenditures, and were not allowed to use the LIFO method. Prior research indicates that the non-current asset revaluations and the capitalisation of research and development costs are value relevant in the Australian capital market (e.g., Barth *et al.* Clinch 1998; Jones 2003). Furthermore, Materials and Energy industries with a high degree of heterogeneity in accounting method choices (e.g., Defond *et al.*; Hung, 2003) constitute a larger portion of the Australian capital market compared to the US market. These differences affect the level of informativeness of discretionary accruals in the Australian context.

To address the research question, a sample of 340 Australian firms over 1992-2004 is analysed. To separate accruals into discretionary and non-discretionary components, the forward-looking model proposed by Dechow *et al.* (2003) is employed. To evaluate the forecasting performance of the regression models, both within-sample and out-of-sample forecasting tests are used. First, the explanatory power of the models is evaluated via the adjusted R^2 for the within-sample period of 1992-2001. The forecast accuracy of the models is then examined by estimating Theil's *U*-statistic and its proportions for the out-of-sample period 2002-2004. In addition, given Hribar and Collins's (2002) findings, this study uses the cash flow approach to estimate total accruals.

This study contributes to the literature in two ways. First, by using Australian data, this study provides the first evidence on the role of discretionary accruals in the predictive ability of earnings for future cash flows using *actual* cash flow components instead of *aggregate* cash flow from operations. This study also extends the methodology used in Subramanyam (1996). To mitigate the limitations of the Jones (1991) model, this study uses both the modified Jones model and the forward-looking model, an alternative model proposed by Dechow *et al.* (2003). Dechow *et al.* (2003) provide evidence that this model is more effective than the Jones (1991) model in estimating discretionary and nondiscretionary accruals.

Second, this study relates to a growing body of accounting literature on the relevance of accounting data in forecasting future cash flows. To date, research in this area has mostly concentrated on the relative predicative ability of aggregate cash flow from operations and earnings (e.g., Bowen *et al.*, 1986; Dechow *et al.*, 1998; Subramanyam and

Venkatachalam, 2007). However, the role of earnings components (that is, cash flows from operations and accruals) in the predictive ability of earnings to forecast future cash flows is not fully understood. Barth *et al.* (2001) provide the first evidence on the role of accrual components in the forecast of future cash flows. Cheng and Hollie (2008) document that incorporating *estimated* operating cash flow components in Barth *et al.*'s model significantly improves the forecast of future cash flows. We extend this strand of literature by demonstrating that decomposing accruals into discretionary and nondiscretionary accruals further improves the predictive ability of earnings for future cash flows.

The remainder of the paper is organised as follows. Section 2 present the research design and Section 3 describes the sample. Section 4 discusses the main results, and section 5 analyses these results with sensitivity tests. Section 6 concludes.

2. Research method

To investigate whether disaggregating earnings into cash flow from operations and accruals, and whether disaggregating accruals into discretionary and nondiscretionary accruals improves the predictive ability of earnings for the forecast of future cash flows, the following linear regression models are employed:

$$CFO_{it} = \alpha_0 + \alpha_1 EARN_{it-1} + \varepsilon_{it} \quad (1)$$

$$CFO_{it} = \beta_0 + \beta_1 CFO_{it-1} + \beta_2 TAC_{it-1} + \varepsilon_{it} \quad (2)$$

$$CFO_{it} = \delta_0 + \delta_1 CFO_{it-1} + \delta_2 DA_{it-1} + \delta_3 NDA_{it-1} + \varepsilon_{it} \quad (3)$$

where *i* and *t* denote firm and year, respectively; *CFO* is cash flow from operations; *EARN* is earnings before extraordinary and discontinuing items; *TAC* is total accruals, i.e., the difference between *EARN* and *CFO*; *DA* is discretionary accruals; and *NDA* is nondiscretionary accruals.

To examine whether the inclusion of the direct method cash flow components enhances the predictability of earnings in Model (3), Model (4) is constructed and its predictability is compared with that of Model (2). This study follows Clinch *et al.* (2002) and Orpurt and Zang (2009) in the selecting cash flow components [3], [4].

$$CFO_{it} = \gamma_0 + \gamma_1 CSHRD_{it-1} + \gamma_2 CSHPD_{it-1} + \gamma_3 INTPD_{it-1} + \gamma_4 TXPD_{it-1} + \gamma_5 OTHCSH_{it-1} + \gamma_6 DA_{it-1} + \gamma_7 NDA_{it-1} + \varepsilon_{it} \quad (4)$$

where *i* and *t* denote firm and year, respectively; *CFO* is cash flow from operations; *CSHRD* is cash received from customers; *CSHPD* is cash paid to suppliers and employees. *INTPD* is net interest paid, i.e., the difference between interest paid and interest received; *TXPD* is taxes paid; and *OTHCSH* is other cash flows from operations, i.e., *OTHCSH* = *CFO* – (*CSHRD* – *CSHPD* – *INTPD* – *TXPD*). The definitions of the other variables are as in Model (3).

To break up total accruals into discretionary and nondiscretionary accruals, the forward-looking model, proposed by Dechow *et al.* (2003), is applied. Dechow *et al.* (2003) indicate that their model has higher explanatory power than the modified Jones model (Dechow *et al.*, 1995) and, in turn, the original Jones (1991) model. Thus, in this study, to mitigate the level of misspecification in estimating discretionary and nondiscretionary accruals, the forward-looking model is employed [5]. The discretionary and nondiscretionary accruals are calculated in this model as follows:

$$NDA = \alpha_1 + \alpha_2\left((1+K)\Delta REV_{it} - \Delta AR_{it}\right) + \alpha_3 PPE + \alpha_4 LAGTAC_{it} + \alpha_5 GR\_REV + \varepsilon_{it} \quad (5)$$

where *i* and *t* denote firm and year, respectively; *NDA* is nondiscretionary accruals; ΔREV is the change in revenues during the year; ΔAR is the change in accounts receivable during the year; *PPE* is the end of year gross property plant and equipment; *K* is the slope coefficient of the regression: $\Delta AR = \alpha + K\Delta REV + \varepsilon$; *LAGTAC* = lagged total accruals; *GR_REV* is the change in revenue from the current year to the next year, scaled by current sales; $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ are the slope coefficients from the following model:

$$TAC = a_1 + a_2\left((1+K)\Delta REV_{it} - \Delta AR_{it}\right) + a_3 PPE + a_4 LAGTAC_{it} + a_5 GR\_REV + \varepsilon_{it} \quad (6)$$

Discretionary accruals are calculated as:

$$DA = TAC - NDA \quad (7)$$

Ordinary least squares (OLS) regression models are used on a pooled time-series of cross sectional data. White's (1980) heteroscedasticity-corrected variances and standard errors are applied in order to correct standard errors in the presence of heteroscedasticity. To address the issue of whether the one-year lagged *CFO* and discretionary and non-discretionary accruals capture different information about the current year operating cash flows, the equality of the coefficients is tested using the chi-square (hereafter χ^2) test. To assess the forecasting ability of the models, the adjusted R^2 for 1992-2001 is estimated. The value of this within-sample goodness of fit measure implies the extent to which a proposed model can explain the total variation of future cash flows.

Out-of-sample forecasting tests are used in addition to within-sample tests, because a higher adjusted R^2 does not necessarily represent a superior predictive ability of a model (Watts and Leftwich, 1977). Accordingly, Theil's *U*-statistic is employed as a forecast error measure as per Kim and Kross (2005) and Bandyopadhyay *et al.* (2010). In particular, the forecast accuracy of aggregate and disaggregated earnings is compared (Models (1) through (4)) during the period of 2002-2004. Theil's *U*-statistic is decomposed into bias, variance, and covariance proportions. In a good prediction, the covariance proportion, which represents unsystematic error, is greater than the bias and variance proportions. The bias proportion indicates systematic error, and the variance proportion signifies the extent to which the fitted series aligns with the actual series. The Theil's *U*-statistic falls between zero and one, with values closer to zero signifying higher forecasting accuracy (Pindyck and Rubinfeld, 1998).

3. Sample and descriptive statistics

The sample is selected from companies listed on the Australian Securities Exchange (ASX) for the years 1992-2004. The related data are obtained from the *Aspect Financial Analysis* database. The sample period begins in 1992, the first year Australian firms were required to report cash flow statements under AASB 1026 (AASB, 1991). The sample ends in 2004 to avoid any structural change in the data because, effective 1 January 2005, Australia adopted the IFRS. CFO is the annual amount of net cash flow from operating activities, as reported in the cash flow statement. Earnings are as reported in the income statement, and measured at net income before extraordinary items and discontinued operations. The cash flow components are collected from the cash flow statement. The accrual components are measured from balance sheet information. Similar to Krishnan and Largay (2000), the variables are scaled by the number of outstanding ordinary shares.

The sample excludes firms in the Financials sector [6] because the components of financial statements and accounting regulations in this sector are different from other sectors. In order to control for potential changes in sample characteristics, each firm is required to have data available for all the variables over the entire sample period. However, this requirement likely introduces a survivorship bias due to the inclusion of larger and more successful firms in the sample. To address this concern, unlike the previous related studies, we do not restrict the sample to a particular company size or specific year-end [7], [8].

As discussed in section 2, the forward-looking model is used to estimate discretionary and nondiscretionary accruals in this study. The regression model is estimated yearly for each one-digit GICS code (excluding GICS code 40 for the Financials sector). Similar to Dechow *et al.* (2003), each industry sector must have at least 10 observations per year. Consequently, firms in the Telecommunication Services and Utilities sectors are excluded from the analysis. Since the total accruals data for 1991 is not available for all sample firms, the model is estimated for the period 1993 to 2004 [9]. Based on these criteria, the initial sample contains 4,080 firm-years representing 340 unique firms. In each regression analysis, the observations with standardised residuals greater than 3 in absolute value are removed [10].

3.1 Descriptive statistics

Table 1, Panel A presents descriptive statistics on market capitalisation, sales, and total assets, as proxies for firm size. The mean (median, standard deviation) of market capitalisation, sales, and total assets are \$1,778.47 (\$19.25, \$2,156.26) million, \$807.72 (\$9.54, \$6,198.19) million, and \$782.88 (\$19.68, \$4,642.8) [11] million, respectively. Therefore, the standard deviations are noticably larger than the respecitve means. This suggests a substantial variation with respect to firm size within the sample, signifying that the sample is not dominated by large firms. The sample, however, contains a small number of very large firms, as suggested by a smaller median compared to the mean in each measure. These sample characteristics are consistent with Clinch *et al.* (2002) [12].

Table 1. Summary statistics of sample by size and industry

Panel A: Sample size

	Market capitalization	Sales	Total assets
Mean	1778.47	807.72	782.88
Median	19.25	9.54	19.68
Std. Dev.	2156.26	6198.19	4642.8

Panel B: Sample composition by industry sector

Industry sector	Number of firms	Sample composition by industry sector	Market composition by industry sector
Energy	33	9.46%	11.36%
Materials	141	40.40%	36.41%
Industrials	54	15.47%	13.49%
Consumer Discretionary	54	15.47%	11.43%
Consumer Staples	24	6.88%	3.99%
Health Care	18	5.16%	10.43%
Information Technology	16	4.58%	8.57%
Telecommunication	6	1.72%	1.68%
Utilities	3	0.86%	2.64%
Total sample	349	100.00%	100.00%

The total sample for sales and total assets comprises 4,537 firm-year observations during the period of 1992-2004. The total sample for market capitalization consists of 3,141 firm-year observations during the period of 1996-2004.
The sample composition by industry sector (Panel B) is based on the initial sample containing 349 firms. Industry sectors are defined by two-digit GICS codes as follows: Energy (10), Materials (15), Industrials (20), Consumer Discretionary (25), Consumer Staples (30), Health Care (35), Information Technology (45), Utilities (55), and Telecommunication (50). Market composition is estimated based on the number of the listed firms on the ASX capital market in 1992 by industry sectors, excluding firms in Financials sector. The data is extracted from the *Aspect Financial Analysis* database.

Panel B of Table 1 reports a comparison of the sample composition and the ASX market (the population) composition in terms of industry sectors. The results indicate that the sample componsition follows the overall sector compostion of the ASX, based on the number of listed firms.

Table 2, Panel A presents descriptive statistics of the slope coefficients for the forward-looking model provided by estimating 84 one-digit GICS-year regressions. The mean and median of PPE are negative, as expected, because depreciation and amortisation expenses, which are associated with PPE, are income-decreasing accruals. The mean and median of the slope coefficient for ((1+*K*) Δ*REV* – Δ*AR*) are negative. However, either positive or negative signs for this parameter are expected, as income-increasing changes in some working capital accounts (e.g., increases in accounts receivable) and income-decreasing changes in others (e.g., increases in accounts payable) may be associated with a change in revenue (Jones, 1991). Consistent with Dechow *et al.* (2003), the mean and median of *LAGTAC* coefficient (0.234 and 0.150, respectively) are positive and their magnitudes are higher than the mean and median of other slope coefficients. The coefficient on *GR_REV* is 0.006 on average, and its median is 0.000. These reveal that the impact of this variable appears to be the lowest on estimating discretionary and non-discretionary accruals compared to other variables.

Table 2, Panel B reports the descriptive statistics for the sample. The mean (median) value of $0.203 ($0.005) per share for cash flow from operations (*CFO*) is larger than the mean (median) for earnings (*EARN*) which is $0.078 ($-0.002) per share [13]. This is mainly because of non-cash expenses (e.g., depreciation expense) included in the variable. Furthermore, the standard deviation of *CFO* is 0.638, higher than that of *EARN* (0.319). This implies that the accrual process mitigates a substantial portion of *CFO* fluctuations. The mean and median for *TAC* are negative, indicating that total accruals have an income-decreasing effect. Consistent with Subramanyam (1996), the mean and median for discretionary accruals (*DA*) are close to zero.

Table 2. Descriptive statistics

Panel A: Descriptive statistics of parameter estimates for forward-looking model

Independent Variables	Mean	Median	Standard Deviation
Intercept	-0.009 (-3.93)	-0.003 (-1.49)	0.059
(1+*K*) Δ*REV* – Δ*AR*	-0.038 (-5.49)	-0.009 (-1.03)	0.326
PPE	-0.116 (-14.97)	-0.054 (-9.36)	0.337
LAGTAC	0.234 (21.14)	0.150 (4.39)	0.585
GR_REV	0.006 (2.089)	0.000 (0.98)	0.093

Panel B: Descriptive statistics for model variables

Variable	Mean	Median	Std.Dev
EARN	0.078	-0.002	0.319
TAC	-0.107	-0.014	0.464
DA	0.002	0.004	0.331
NDA	-0.109	-0.028	0.319
CFO	0.203	0.005	0.638
CSHRD	2.651	0.157	6.726
CSHPD	2.416	0.147	6.429
INTPD	0.020	0.000	0.125
TXPD	0.044	0.000	0.124
OTHCSH	0.034	0.000	0.500

Forward looking model: $TAC = a_1 + a_2((1+K)\Delta REV_{it} - \Delta AR_{it}) + a_3 PPE + a_4 LAGTAC_{it} + a_5 GR\_REV + \varepsilon_{it}$

Coefficient estimates are calculated from the related 84 one-digit GICS-year regressions. Figures in parentheses refer to means/medians of regression *t*-statistics.Variable definition: *TAC* refers to total accruals; Δ*REV* is the change in revenues during the year; Δ*AR* is the change in accounts receivable during the year; *PPE* is the end of year gross property, plant and equipment; *LAGTAC* is the lagged value of total accruals; *K* is the slope coefficient extracted from this regression: $\Delta AR = \alpha + K\Delta REV + \varepsilon$ for each one-digit GICS-year grouping; *GR_REV* is the change in revenue for the next year, scaled by current revenue. *CFO* is cash flow from operations; *EARN* is earnings; *DA* and *NDA* are discretionary and nondiscretionary accruals, respectively; *CSHRD* is cash received from customers; *CSHPD* is cash paid to suppliers and employees; *INTPD* is net interest paid; *TXPD* is taxes paid; *OTHCSH* is other cash flows from operations. All variables are scaled by the number of ordinary shares outstanding. The total sample consists of 4,080 firm-year observations during the period 1993-2004.The variables with the exception of *GR_REV* are scaled by the number of ordinary shares outstanding. The sample period is 1993-2004.

The mean and median values of the nondiscretionary accrual component of *TAC* are also considerably higher than those of its discretionary counterpart, but *DA* is more variable than *NDA*. The mean (median and standard deviation) values of *CSHRD* and *CSHRD* are $2.651 ($0.157, $6.726) and $2.416 ($0.147, $6.429), respectively, all of which are larger than that of *INTPD*, *TXPD*, and *OTHCSH*. Thus, the predictive ability of *CFO* would be considerably affected by *CSHRD* and *CSHPD*.

4. Empirical results

The analyses in this section explain whether disaggregating earnings into cash flow from operations, discretionary accruals, and nondiscretionary accruals improves the predictive ability of earnings for the forecast of future cash flows. Panel A of Table 3 reveals that the slope coefficients on one-year lagged *CFO* and *TAC* are significantly and positively related to current cash flow from operations at the 0.01 and 0.05 levels, respectively. The magnitude of *TAC* (0.40) is less than *CFO* (0.94), which implies that *CFO* has greater contribution than *TAC* in explaining future cash flows. The adjusted R^2 for Model (2) is 49%, which is higher than the adjusted R^2 of Model (1) (35%). Results from tests of coefficient restrictions reveal that the equality of *TAC* to *CFO* is rejected at the 0.01 level (χ^2 statistic = 21.12). These results suggest that *CFO* and *TAC* together provide a significantly better explanation for the variation of current *CFO* than *EARN* alone. The slope coefficients on *CFO* and *DA* are significant at the 0.01 level. The coefficient on *NDA* is marginally significant at the 0.10 level. Consistent with Subramanyam (1996), the coefficient magnitude of *DA* (0.49) is higher than that of *NDA* (0.23), and both coefficients are positive.

The adjusted R^2 value for one-year lag Model (3) is 53%, which is higher than that of Models (1) and (2). Results from tests of coefficient restrictions indicate that the coefficient estimates on *CFO*, *DA* and *NDA* are significantly different from each other at the 0.01 level (χ^2 statistic = 30.60). Moreover, discretionary and nondiscretionary accruals significantly differ in that they do not equal zero at the 0.01 level.

Table 3. Predictive ability of cash flow, discretionary and nondiscretionary accruals

$$\text{Model (1)}: CF_{it} = \alpha_0 + \alpha_1 EARN_{it-1} + \varepsilon_{it}$$
$$\text{Model (2)}: CF_{it} = \beta_0 + \beta_1 CFO_{it-1} + \beta_2 TAC_{it-1} + \varepsilon_{it}$$
$$\text{Model (3)}: CFO_{it} = \theta_0 + \theta_1 CFO_{it-j} + \theta_2 DA_{it-j} + \theta_3 NDA_{it-j} + \varepsilon_{it}$$

Panel A: Summary of results for within-sample forecasting tests (2,720 firm-years, 1993-2001)

	Model (1)		Model (2)		Model (3)	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	0.09	8.59†	0.05	7.21†	0.04	4.18†
EARN	1.027	14.07†				
CFO			0.94	11.59†		
TAC			0.40	2.58†	0.90	13.91†
DA					0.49	4.24†
NDA					0.23	1.67*
Adjusted R^2	35%		49%		53%	
Tests of Coefficient Restrictions						
Null hypothesis		χ^2 statistic	*p*-value			
$B_1 = \beta_2$		21.12	0.00			
$\theta_1 = \theta_2 = \theta_3$		30.60	0.00			
$\theta_2 = \theta_3$		5.94	0.01			
$\theta_2 = \theta_3 = 0$		20.14	0.00			

Panel B Summary of results for out-of-sample forecasting tests (2002-2004)

Forecast Performance Measures	Model (1)	Model (2)	Model (3)
Theil's *U*-statistic	0.53	0.38	0.32
Bias proportion	0.00	0.01	0.01
Variance proportion	0.02	0.05	0.13
Covariance proportion	0.98	0.95	0.86
N	1,020	1,020	1,020

Variable definition: *CFO* is cash flow from operations; *DA* is discretionary accruals; *NDA* is nondiscretionary accruals. *i* and *t* denote firm and year, respectively; *j* ranges 1 and 2. See text for the full description of Models 1 to 3. The *t*-statistic is based on the White (1980) robust standard errors. Theil's *U*-statistic is a forecast error statistic, which lies between zero and one, when one shows the worst fit. In a good forecast, the bias and variance proportions of Theil's *U*-statistic are smaller than the covariance proportion. † Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.10 level. N is the number of observations included for analysing within-sample (Panel A) or out-of-sample (Panel B) forecasting tests.

These results suggest that disaggregating *EARN* into the aforementioned components are more informative in explaining future cash flows than *EARN* alone. Also, *DA* and *NDA* have incremental information content over and above that contained in *CFO* and *TAC*.

Panel B of Table 3 exhibits the results of the out-of-sample forecasting tests. The variance and bias proportions are lower than the covariance proportion across all models. Thus, Models (1), (2), and (3) can predict future cash flows properly. Theil's *U*-statistic of 0.32 in Model (3) is lower than that of Models (1) and (2). Hence, earnings disaggregated into cash flow from operations, discretionary accruals, and nondiscretionary accruals, have higher predictive ability for forecasting future cash flows than earnings alone, or when earnings are disaggregated into cash flow from operations and total accruals [14].

4.1 Incremental predictive ability of direct method cash flow components

Panel A of Table 4 reports the within-sample forecasting statistics for Model (4). Slope coefficients on CSHPD, CSHRD, INTPD, OTHCSH, DA, and NDA in one-year lag Model (4) are significant at either the 0.05 or 0.01 level. However, the coefficient on TXPD is not significant at conventional levels. The coefficients on DA and NDA are positive, but the magnitude of the DA coefficient is lower than that of the NDA coefficient. This is not consistent with the results of Model (3), in which DA is more persistent than NDA in predicting future cash flows. The coefficient on CSHRD is positive and the coefficients on CSHPD and INTPD are negative as expected. Results from χ^2 tests of coefficient restrictions reject the null hypothesis that the coefficients on cash flow components are equal to zero (χ^2 statistic = 430.88) or equal to each other (χ^2 statistic = 97.20) at the 0.01 level. The results also show that DA and NDA significantly differ from zero (χ^2 statistic = 139.77) or differ from each other (χ^2 statistic = 631.50) at the 0.01 level.

Table 4. Predictive ability of cash flow components and discretionary and nondiscretionary accruals

$$\text{Model}(4): CFO_{it} = \gamma_0 + \gamma_1 CSHRD_{it-1} + \gamma_2 CSHPD_{it-1} + \gamma_3 INTPD_{it-1} + \gamma_4 TXPD_{it-1} + \gamma_5 OTHCSH_{it-1} + \gamma_6 DA_{it-1} + \gamma_7 NDA_{it-1} + \varepsilon_{it}$$

Panel A: Summary of results for within-sample forecasting tests (2,720 firm-years, 1993-2001)

Variable	Model (4)	
	Coefficient	*t*-statistic
Intercept	0.01	3.97†
CSHRD	0.40	4.91†
CSHPD	-0.39	-7.72†
INTPD	-0.77	-4.05†
TXPD	0.27	0.83
OTHCSH	0.49	10.18†
DA	0.14	2.01**
NDA	0.31	2.36**
Adjusted R^2	60%	
Adjusted R^2 – Model (1)	35%	
Adjusted R^2 – Model (2)	49%	
Adjusted R^2 – Model (3)	53%	

Tests of Coefficient Restrictions:

Null Hypothesis	X^2 statistic	*p*-value
$H_{0\text{-}1}$: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = 0$	430.88	0.00
$H_{0\text{-}2}$: $\gamma_6 = \gamma_7 = 0$	139.77	0.00
$H_{0\text{-}3}$: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5$	97.20	0.00
$H_{0\text{-}4}$: $\gamma_6 = \gamma_7$	631.50	0.00

Panel B: Summary of results for out-of-sample forecasting tests (2,720 firm-years, 2002-2004)

Forecast Performance Measures	Model (1)	Model (2)	Model (3)	Model (4)
Theil's *U*-statistic	0.53	0.37	0.32	0.30
Bias proportion	0.00	0.01	0.01	0.00
Variance proportion	0.01	0.07	0.13	0.04
Covariance proportion	0.99	0.92	0.86	0.96

i and *t* denote firm and year respectively. *CFO* is net cash flow from operating activities under the cash flow statement. *CSHRD* is cash received from customers. *CSHPD* is cash paid to suppliers and employees. *INTPD* is net interest paid. *TXPD* is taxes paid. *OTHCSH* is other cash flows from operations. See text for full description of Models (1) to (3). The *t*-statistics is based on White's (1980) robust standard errors. Theil's *U*-statistic is a forecast error statistic that lies between zero and one, when one shows the worst fit. In a good prediction, the bias and variance proportions of Theil's *U*-statistic are smaller than its covariance proportion. † indicates significance at the 0.01 level. ** indicates significance at the 0.05 level.

Therefore, cash flow from operation, discretionary accurals and nondiscretioanry accruals - all have significant roles in explaining the variations of current *CFO*. The adjusted R^2 of Model (4) is 60%, which is higher than that of Model (3) (53%). The adjusted R^2 of Model (4) is also significantly higher than that of Models (1) and (2). Therefore, the components of *CFO*, and *DA* and *NDA*, taken together can better explain future cash flows than aggregate *CFO*, *DA* and *NDA* taken together or than the combination of *CFO* and *TAC*.

The results of out-of-sample forecasting are consistent with the within-sample forecasting results. As shown in Panel B of Table 4, the bias and variance proportions of Theil's *U*-statistic for Model (4) are lower than the covariance proportion, implying that the model can forecast future cash flows well. Further, Theil's *U*-statistic of Model (4) is 0.30, which is lower than that of Model (3) (0.32). Hence, direct cash flow components, *DA* and *NDA* together have better predictive ability than using *CFO*, *DA* and *NDA* for future cash flows. Theil's *U*-statistic of Model (4) is also lower than that of Models (1) and (2), confirming that the predictive ability of *EARN* to forecast future cash flows is enhanced when the components of both cash flow from operations and accruals are allowed to vary in the forecasting model, relative to aggregate *CFO* and *TAC*.

5. Further robustness checks

In unreported tests, the regression models are estimated using a random-effects method. This is to overcome, at least partially, the significant limitation of the OLS method where both intercepts and coefficients are constant. The results support the inferences from OLS regressions. It can be noted that the explanatory powers of the forecasting models significantly increase. It implies that the random-effects method can better control unobserved omitted variables and thus eliminate a larger fraction of the variation in current cash flow, compared with the OLS method.

The main findings are also robust to other sensitivity tests (untabulated) as follows: (i) re-estimating the regression models after deflating variables based on average total assets, as per Subramanyam (2001); (ii) re-estimating discretionary and nondiscretinary accruals based on the modified Jones model; (iii) re-estimating regression models across years to control for possible autocorrelations in the residuals, as per Barth et al. (2001); and (iv) using two-year lagged accounting variables to predict current cash flows.

The Pearson correlation coefficients (unreported) for the full sample also indicate that *CSHRD* is highly correlated (r = 0.99) with *CSHPD*. To mitigate potential multicollinearity problems arising from this issue, the regression models are re-examined after combining *CSHRD* and *CSHPD* into a single variable (see Gujarati 2003). The results remain unaltered. The one- and two-year lags for Model (4) are also re-estimated after dropping cash paid to suppliers and employees. The predictive ability of the models to forecast future cash flows decreases after the exclusion of *CSHPD*. Maddala (2001, p. 278) argues that multicollinearity is not a serious problem for prediction if the prediction of the model (here Model (4)) is higher than that of a model that includes only a subset of the explanatory variables (here variables in Model (4) excluding *CSHPD*). Given Maddala's guidance, we conclude that multicollinearity is not a serious problem in model (4).

6. Conclusion

This study provides evidence for the relative usefulness of discretionary and nondiscretionary accruals in the predictive ability of earnings for future cash flows in Australia. Our analysis of actual cash flow components data has a unique advantage over U.S. studies in this area. We avoid aggregation bias and model misspecification as suffered by Subramanyam (1996).

The forecasting performance of our regression models is evaluated based on both within-sample forecasting tests (i.e., adjusted R^2) for the period 1992-2001 as well as out-of-sample forecasting tests (i.e., Theil's *U*-statistic and its proportions) for 2002-2004. The results generally suggest that disaggregating earnings into cash flow from operations, discretionary accruals, and nondiscretionary accruals is more relevant than aggregate earnings in future cash flow prediction. Discretionary and nondiscretionary accruals together provide incremental predictive power over and above that provided by total accruals. The relative contribution of discretionary accruals is also more than that of nondiscretionary accruals in predicting future cash flows. However, allowing coefficients on cash flow components to vary dims the relative usefulness of discretiarny accruals. Hence, it is likely that the models based on aggregate cash flow from operations rather than direct method cash flow components may suffer from aggregation bias, and thus the models based on aggregated cash flow are likely to be misspecified.

The implication of our findings is that Australian companies, on average, use their discretionary accounting choices to increase the predictive power of earnings in the forecast of future cash flows. The results of this study extend, in part, Subramanyam (1996) by showing that his related findings are robust in the use of the cash flow approach in estimating total accruals, and in the application of a more powerful accrual model (i.e, forward-looking model) than the Jones and modified Jones models in estimating discretionary accruals. The findings in this study also support the recent view among accounting standard-setters that direct method cash flow statements should be mandated, as aggregate cash flow data alone is insufficient to fully understand future cash flows [15].

Collectively, this study also provides additional insights into the 'uniformity versus flexibility' argument in generally accepted accounting principles. While managerial discretion, due to the flexibility provided by accounting standards, can be used opportunistically in earnings management, such discretion may enhance the usefulness of earnings by allowing managers to communicate their inside information on expected future cash flows (e.g., Subramanyam, 1996). By showing that discretionary accruals enhance the predictive ability of earnings to forecast future cash flows, this study supports the view that managerial discretion improves, rather than distorts, the relevance of earnings to accounting users in the Australian capital market setting.

Notes:

1. See *Conceptual Framework for Financial Reporting* (International Financial Reporting Standards [IFRS] Foundation 2010a, para. OB3); Statement of Financial Accounting Concepts No. 1, *Objectives of Financial Reporting by Business Enterprises* (FASB, 1978, paras 37–39).
2. All data used in this study come from the pre-IFRS period (i.e, 1992–2004); during this period Australian firms were mandated to disclose direct method cash flow information under Australian Accounting Standards Board (AASB) 1026, *Statement of Cash Flows* (AASB, 1991, revised 1997). This standard was withdrawn in January of 2005 and replaced by AASB 107, *Cash Flow Statements* (AASB, 2004), which is equivalent to IAS 7 (IASC, 1992).
3. Some other related studies use slightly different sets of CFO components. For example, Krishnan and Largay (2000) include interest paid and interest received rather than net interest paid, but do not use other operating cash flows in their prediction models. Cheng and Hollie (2008) include operating expense as a separate item in their cash flow classification.
4. We use an alternative set of direct method CFO components to assess Model (4), that is, cash received from customers, cash paid to suppliers and employees, interest received, interest paid, taxes paid, dividends received, and other cash flows. The conclusions based on this alternative set of variables remain unaltered.
5. Various models are developed to estimate nondiscretionary accruals; however, all of them are subject to misspecification in some way. Dechow *et al.* (1995) evaluate the power of five competing models in estimating discretionary and nondiscretionary accruals relating to earnings management. They conclude that while none of the models works perfectly in computing discretionary accruals, the modified Jones model is the least biased among the five models.
6. Sector is the first level of industry classification in the Global Industry Classification Standard (GICS) system. The GICS system comprises 10 economic sectors, 23 industry groupings, 59 industries, and 122 sub-industries.
7. For example, Barth *et al*. (2001) and Cheng and Hollie (2008) exclude firms with sales of less than US $10 million and share prices of less than US $1, whilst all these firms are included in the present study if they have all the required data for the study period.
8. We compare the sample firms to the market firms for each year using the mean and median values of sales, total assets and market capitalisation as proxies of size. The results of the *t*-test and the Mann-Whitney *U*-test (unreported) suggest that overall our sample firms do not significantly differ from the market firms in terms of size.
9. To provide comparability among prediction models, the values of total accruals (*TAC*), the change in revenues during the year (ΔREV), the change in accounts receivable during the year (ΔAR), and the end of year gross property, plant and equipment (*PPE*) are scaled by the number of ordinary shares outstanding, consistent with other variables in this study.
10. We repeat our analysis by removing the observations with the extreme upper and lower one percent of earnings and cash flow as in Barth *et al.* (2001). The results are not influenced by their exclusion.
11. All financial figures in this paper are in Australian dollars unless otherwise specified.
12. The median values for market capitalisation, sales, and total assets in Clinch *et al.* (2002) are relatively larger than those reported in this paper. This, is, however, expected, as their sample is restricted to companies with market values exceeding $10 million.
13. The negative median of *EARN* contrasts with the positive median of *EARN* found in most related US studies. The reason for this dissimilarity may lie in the fact that the extent of loss incidence in Australian firms listed in the ASX is generally high, as evidenced by Balkrishna *et al.* (2007). Further, the US studies mostly focus on large firms, which are typically more profitable than smaller firms are. Untabulated results show that *EARN* is positive (negative) for 49% (51%) of the sample. Hence, in this sample, there is no overall bias to profitable or unprofitable firms.
14. Results reported in this section qualitivatively remain unchanged after re-estimating discretionary and nondiscretinary accruals based on the modified Jones model (Dechow *et al.*, 1995) as well as using average total assets as an alternative deflator.
15. See the joint FASB/IASB project on "Financial Statement Presentation" (IFRS Foundation, 2010b, FASB, 2010).

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