International Research Journal of Finance and Economics
ISSN 1450-2887 Issue 97 September, 2012

http://www.internationalresearchjournaloffinanceandeconomics.com

Further Evidence on the Relative Forecast Ability of Earnings and Cash Flows: An Industry-Level Analysis

Shadi Farshadfar
Ted Rogers School of Management, Ryerson University
Toronto, Ontario, Canada M5B 2K3
E-mail: sfarshadfar@ryerson.ca
Tel: +1-416-9795000; Fax: +1-416-9795266

Abstract

This paper provides further evidence on the relative importance of accrual-based earnings and cash flow from operations as reported under the cash flow statement in the Australian context with respect to a firm's future cash flows. Specifically, it presents an empirical investigation of the extent to which industry membership can help explain the variability in cash flow from operations and accrual earnings usefulness in the forecast of future cash flows**.** Both within-sample and out-of-sample forecasting methods are used to test the predictability of the forecasting models. The findings suggest that cash flow from operations reported under the cash flow statement has higher predictive ability than accrual earnings in the forecast of future cash flows irrespective of industry groupings. However, the level of the forecasting ability of both earnings and cash flow from operations varies across industries. In particular, the results reveal that earnings are not a relevant predictor of future cash flows in the Energy and Materials industry sectors; cash flow from operations is more useful to market participants in these industries. Additionally, the predictive abilities of both earnings and cash flow from operations are lowest in the Health Care and Information Technology sectors.

Keywords: Forecasting Future Cash Flows, Earnings, Cash Flow from Operations, Australia

1. Introduction

This study provides further evidence on the relative ability of accrual-based earnings and cash flow from operations reported under the cash flow statement in the forecast of future cash flows in Australian firms. It aims to examine the extent to which industry characteristics influence the relative usefulness of earnings and cash flow from operations in the forecast of future cash flows.

Accrual earnings and cash flow from operations as summary measures of a firm's performance has been the subject of ongoing evaluation by accounting researchers. There are theoretical debates in favour of both measures. As argued by Dechow (1994), cash flow from operations can be used as a measure of performance due to the fact that the ability of a firm to generate cash receipts beyond cash payments represents its success. However, cash flow from operations suffers from timing and matching problems over finite periods. As a result, accrual accounting introduces earnings as an alternative performance measure. Earnings is adjusted cash flow from operations achieved via the accrual process. This accrual process complies with two important accounting principles: revenue recognition and matching principles. Supporters of accrual-based earnings deem that the accrual process, through these two fundamental accounting principles, mitigates timing and matching problems in cash flow from operations. Consequently, earnings is a better indicator of a firm's performance, and thus is more useful than cash flow from operations in predicting future cash flows. Nevertheless, accruals are affected by different policies, resulting in measurement variation in earnings. In other words, earnings are likely to involve some judgment, and can therefore be a poor indicator of future cash flows if the accruals are used opportunistically to manipulate earnings rather than to enhance their information content. For example, managers may have incentives to manipulate earnings if their reward systems are based on accounting performance (DeAngelo, 1986; Healy, 1985). In this respect, the Financial Accounting Standards Board (FASB) asserts that information about earnings and its components is a better predictor of future cash flows than cash flows themselves (FASB, 1978, para. 43, 44). The International Accounting Standard Board does not make such a claim. However, it maintains that cash flow information, which is reported in the cash flow statement, is able to assess future cash flows in conjunction with information provided by the income statement and the balance sheet (IASC, 1992, para. 13).

Several studies have investigated the comparative relevance of aggregate earnings and cash flow from operations in predicting future cash flows to provide evidence for the above claim. The findings of earlier studies using *estimated* cash flow from operations are mixed (e.g., Bowen et al., 1986; Greenberg et al., 1986; Dechow et al., 1998). However, more recent studies using *reported* cash flow from operations (e.g., Barth et al. 2001; Subramanyam and Venkatachalam, 2007; Farshadfar et al., 2008; Habib, 2010) indicate that reported cash flow from operations is a better predictor of future cash flows than earnings. One possible reason for the mixed results of earlier studies in this area is the use of estimated rather than actual figures of cash flow from operations; prior research (e.g., Austin and Bradbury, 1995; Hribar and Collins, 2002) demonstrates that even the best estimations of cash flow from operations produce large errors. These studies conclude that estimated cash flow from operations, used frequently in prior research, may not be an adequate surrogate for cash flow from operations under the cash flow statement.

Previous research in this area has also been mostly confined to US firms. Given that the quality of a country's accounting information is mostly influenced by its unique institutional setting (e.g., Ball 2000; Bartov et al. 2001), the generalizability of the US findings to other regulatory jurisdictions may be limited. The Australian reporting jurisdiction, which introduced the cash flow statement in 1992 under AASB 1026 (AASB, 1991, revised 1997)[1], provides another important context in which to re-examine the relative predictive ability of earnings and reported cash flow from operations for future cash flows. The Australian empirical evidence in this area, however, is limited. Percy and Stokes (1992) document that the traditional measures of cash flows (i.e., net income plus depreciation and amortization; and working capital from operations) are better predictors of future cash flows than *estimated* cash flow from operations and earnings. Their industry analysis reveals that their results are not generalisable across industry categories. Farshadfar et al. (2008) provide evidence for the superior ability of reported cash flow from operations to earnings in the forecast of future cash flows in Australia. They also show that the predictive ability of both earnings and cash flow from operations increases with firm size. In a more recent study, Habib (2010) finds that cash flow from operations has higher predictive ability relative to earnings after controlling for firm size, negative versus positive cash flow pattern, cash flow variability, and firm operating cycle.

This study seeks to extend the cash flow prediction literature by providing an industry-level analysis of the association of accrual earnings and actual cash flow from operations with future cash flows in the Australian context. It is argued that firms' economic conditions and their chosen accepted accounting policies as well as the mix and types of accruals are likely to be industry specific. For example, investments in inventories or fixed assets are much higher in manufacturing firms than they

---

[1] AASB 1026 was withdrawn in January of 2005 and replaced by AASB 107, *Cash Flow Statements* (AASB, 2004). This standard is equivalent to International Accounting Standard 7 (IASC, 1992).

are in service firms. Manufacturing firms also are more likely to have large amounts of receivables than retail firms (Barth et al., 2001; Barth et al., 2005; Gu et al., 2005). In addition, Clinch et al. (2002) maintain that different operating environments across industries in Australia, such as mining firms versus non-mining firms, may affect the informational role of cash data.

The findings of the current study confirm the above and reveal new knowledge on the role of industry on the relative usefulness of earnings and cash flow from operations for market participants. For example, the findings indicate that accrual earnings is a poor predictor of future cash flows in the Energy and Materials industry sectors; cash flow from operations is more useful to market participants in these industries. Additionally, the predictive abilities of both earnings and cash flow from operations are lowest in the Health Care and Information Technology sectors.

The remainder of this article is organised as follows. Section 2 describes the research design. Section 3 presents the sample selection and descriptive statistics. Section 4 discusses the main results. Section 5 provides further analysis. Section 6 concludes the paper.

2. Research Design

To test the predictive ability of cash flow from operations and earnings for future cash flows, the following Ordinary Least Squares (OLS) regression models are estimated on a pooled time-series of cross-sectional data:

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

$$\text{Model (2)}: CFO_{it} = \beta_0 + \beta_1 CFO_{it-1} + \varepsilon_{it}$$

where *i* and *t* denote firm and year included in the sample period (1992-2004); *CFO* is cash flow from operations as reported under the cash flow statement; and *EARN* is earnings before extraordinary and discontinuing items.

White's (1980) heteroscedasticity-corrected variances and standard errors are employed in order to correct standard errors in the presence of heteroscedasticity. To assess the forecasting ability of the models, the explanatory powers of models (1) and (2) are compared using adjusted R^2s for 1992–2001. Vuong's (1989) likelihood ratio test for model selection is then estimated to evaluate whether the explanatory powers of two competing models are significantly statistically different (Dechow, 1994, Appendix 2). To augment the reliability of the results of within-sample forecasting tests,the out-of-sample tests are also employed because a higher adjusted R^2does not necessarily imply a higher forecasting power (Watts and Leftwich, 1977). Accordingly, the forecast accuracy of models (1) and (2) during the period of 2002–2004 is compared using Theil's *U*-statistic, following Kim and Kross (2005) and Farshadfar et al. (2008). Theil's *U*-statistic is a forecast error measure and is decomposed into bias, variance, and covariance proportions. The measures of covariance and bias proportions indicate unsystematic and systematic errors, respectively. The variance proportion signifies the extent to which the fluctuations in the fitted series follow those in the actual series. In a good forecast, the bias and variance proportions are lower than covariance proportion. The Theil's *U*-statistic lies between one and zero, with values closer to one implying lower forecast accuracy (Pyndick and Rubinfeld, 1998).

3. Sample Selection and Descriptive Statistics

The sample is collected from all Australian Stock Exchange (ASX) companies covered in the *Aspect Financial Analysis* database for the period of 1992-2004. The sample period begins in 1992 because Australian companies have been required to report the cash flow statement since 1992. As Australia adopted International Financial Reporting Standards in 2005,2004 is the final year of the sample to avoid any structural change in the data. Only firms with data for earnings and cash flow from operations items over the sample period are included in the sample. Furthermore, companies in the

Financials sector[2] are excluded because their financial statements are subjected to special accounting regulations.

Earnings is net income before extraordinary items and discontinued operations, as reported in the income statement. Cash flow from operations is collected from the cash flow statement. The variables are scaled by the number of outstanding ordinary shares. The sample is not limited to any firm size or specific year-end. Accordingly, the total primary sample contains 4537 firm-years observations from 349 firms. Companies are then classified into industry sectors based on two-digit Global Industry Classification Standard (GICS) codes.[3] Each industry sector is represented by more than ten firms; therefore, Telecommunication Services and Utilities, with six and three companies respectively, are excluded. As a result, the total sample is reduced to 340 firms comprising 4420 firm-year observations across seven industry sectors: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, and Information Technology.

Table 1: Comparison by Industry Sector

Industry sector	Number of firms	Sample composition	ASX market composition
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%**

Industry sector is defined by two-digit GICS code 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 based on the number of listed firms in the ASX in 1992 by industry sector, excluding firms in the Financials sector. The sample composition is based on the initial sample of 349 firms.

The composition of the total sample by industry sector is reported in Table 1. The sample composition overall follows the industry composition of the ASX market composition in terms of the number of firms.Table 2 presents the sample's descriptive statistics for earnings, cash flow from operations, and total assets as a proxy of firm size. The mean (median) earnings per share for Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, and Information Technology are $0.03 ($-0.00), $0.03 ($-0.01), $0.14 ($0.08), $0.16 ($0.09), $0.16 ($0.14), $-0.00 ($-0.10), and $-0.03 ($-0.01) respectively. Thus, the Consumer Discretionary, Consumer Staples, and Industrials sectors appear to be more profitable on average than other industry sectors. The mean (median) cash flow from operations for Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care and Information Technology are $0.07 ($-0.00), $0.05 ($-0.00), $0.26 ($0.15), $0.24 ($0.12), $0.33 ($0.18), $0.07 ($-0.00), and $-0.00 ($-0.01), respectively. Consistent with prior research (e.g., Dechow et al., 1998; Barth et al., 2001), the mean (median) *CFO* values are larger than the mean and median for *EARN* across all industries. This difference is mainly due to the fact that the non-cash expenses such as depreciation and amortisation expense decrease *EARN* but not *CFO*(Cheng and Yang, 2003).

---

[2] Sector is the first level of industry classification in the GICS system. The GICS system comprises 10 economic sectors, 23 industry groupings, 59 industries, and 122 sub-industries.

[3] The analysis in this study is based on two-digit classification because of data limitation: the sample size drops significantly when four-digit classification is applied.

Table 2: Sample Statistics for Model Variables by Industry

Variable	Mean	Median	Standard deviation	N
Energy				428
EARN	0.03	-0.00	0.18	
CFO	0.07	-0.00	0.20	
TA	436.77	11.83	605.22	
Materials				1782
EARN	0.03	-0.01	0.48	
CFO	0.05	-0.00	0.19	
TA	675.39	9.33	1651.709	
Industrials				696
EARN	0.14	0.08	0.35	
CFO	0.26	0.15	0.40	
TA	434.43	39.59	1303.47	
Consumer Discretionary			697	
EARN	0.16	0.09	0.30	
CFO	0.24	0.12	0.34	
TA	343.04	57.87	822.65	
Consumer Staples				312
EARN	0.16	0.14	0.46	
CFO	0.33	0.18	0.33	
TA	4434.71	382.68	14060.69	
Health Care				226
EARN	-0.00	-0.10	0.19	
CFO	0.07	-0.00	0.20	
TA	322.46	20.61	1183.9	
Information Technology			205	
EARN	-0.03	-0.01	0.12	
CFO	-0.00	-0.01	0.06	
TA	56.63	9.89	123.64	

CFO is cash flow from operations reported under cash flow statement; *EARN* is earnings before extraordinary and discontinuing items; *TA* is total assets in $ million (Australian). The total sample for all variables consists of 4,520 firm-year observations during the period 1992-2004. *EARN* and *CFO* are scaled by the number of ordinary shares outstanding at year-end.

The standard deviation of *CFO* is higher than that of *EARN* for the Energy, Industrials, Consumer Discretionary, and Health Care groupings. This implies that the accrual process is able to mitigate a sufficient portion of *CFO* fluctuations in these industry sectors. With respect to firm size, there is substantial variation across industries as well as within industries. The mean (median) total assets are: Energy $436.77 million ($11.83 million), Materials $675.39 million ($9.33 million), Consumer Discretionary $343.04 million ($57.87 million), Consumer Staples $4,434.71 million ($382.68 million), Industrials $434.43 million ($39.59 million), Health Care $322.46 million ($20.61 million), and Information Technology $56.63 million ($9.89 million). Thus, the largest firms are evidently in the Consumer Staples industry.

4. Empirical Results

Table 3 presents summary results of within-sample and out-of-sample forecasting tests according to industry categories. Panel A of Table 3 reveals that all coefficients in models (1) and (2) including intercepts are significant at conventional levels in all industry sectors. The exception is the coefficient on *EARN* for the Information Technology group, which is not statistically significant at conventional levels. As expected, both *EARN* and *CFO* are positively related to future cash flows across all industry groups. The separate industry results reveal that the adjusted R^2s of model (1) (model (2)) for Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, and Information Technology are 22% (68%), 23% (63%), 31% (48%), 40% (52%), 40% (65%), 9% (48%), and 3% (8%), respectively. Vuong's *Z*-statistics for model (1) versus model (2) at industry level are: Energy

10.20, Materials 9.46, Industrials 5.12, Consumer Discretionary 5.25, Consumer Staples 7.14, Health Care 4.65, and Information Technology 3.31. This suggests that the difference between the two adjusted R^2s is statistically significant at the 0.01 level in all industry groups. These results show that both one-year lagged *CFO* and *EARN* are able to explain the variation in current *CFO* at industry level. However, the ability of *CFO* to explain future cash flows is significantly higher than that of *EARN*.

Panel B of Table 3 reports the results of out-of-sample forecasting tests. Theil's *U*-statistic values for model (1) (model (2)) are: Energy 0.50(0.35), Materials 0.61(0.40), Industrials 0.43(0.31), Consumer Discretionary 0.35(0.33), Consumer Staples 0.41(0.29), Health Care 0.71(0.40), and Information Technology 0.86(0.84). Theil's *U*-statistic values for model (1) are noticeably higher than those of model (2) at industry level. These findings support the results of the within-sample forecasting statistics and suggest that *CFO* is a better predictor of future cash flows than *EARN* in all industry sectors. While the findings on the superior predictability of cash flow from operations over earnings are similar to those drawn from previous Australian studies (e.g., Farshadfar et al., 2008; Habib, 2010), the results indicate some systematic industry differences that are worth noting.

Table 3: Predictive Ability of Earnings and Cash Flow from Operations by Industry Sector

$$\text{Model (1)}: CFO_{it} = \alpha_0 + \alpha_1 EARN_{it-1} + \varepsilon_{it}$$
$$\text{Model (2)}: CFO_{it} = \beta_0 + \beta_1 CFO_{it-1} + \varepsilon_{it}$$

Panel A: Summary of results for within-sample forecasting tests (1992-2001)

Variable	Energy	Materials	Industrials	Consumer Discretion.	Consumer Staples	Health Care	Information Technology
Model (1)							
Intercept	0.07**	0.04†	0.16†	0.12†	0.13†	0.06†	-0.01**
EARN	0.61**	0.57†	0.76†	0.75†	0.98†	0.28*	0.06
Model (2)							
Intercept	0.01†	0.01†	0.08†	0.06†	0.06†	0.01**	-0.01**
CFO	0.84†	0.78†	0.71†	0.78†	0.83†	0.55†	0.18†
AdjR^2–M(1)	22%	23%	31%	40%	40%	9%	3%
AdjR^2–M(2)	68%	63%	48%	52%	65%	48%	8%
Vuong's *Z*-statistic M(1) vs. M(2)	10.20†	9.46†	5.12†	5.25†	7.14†	4.65†	3.31†

Panel B: Summary of results for out-of-sample forecasting tests (2002-2004) - Theil'sU-statistic

Industry sector	Model (1)	Model (2)	*N*
Energy	0.50	0.35‡	87
Materials	0.61	0.40‡	407
Industrials	0.43‡	0.31‡	155
Consumer Discretionary	0.35‡	0.33‡	152
Consumer Staples	0.41‡	0.29‡	68
Health Care	0.71	0.40	53
Information Technology	0.86	0.84	41

CFO is cash flow from operations reported under the cash flow statement; *EARN* is earnings before extraordinary items. Theil's*U*-statistic is a forecast error measure that lies between zero and one, when one shows the worst fit. Total included observations for analysing within-sample and out-of-sample forecasting tests at the industry level after the exclusion of outliers are as follows: Energy=404; Materials=1769; Industrials=689; Consumer Discretionary=685; Consumer Staples=291; Health Care=229; Information Technology=174. † Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.10 level. ‡ The covariance proportion is higher than the variance and bias proportions. Vuong's*Z*-statistic is estimated via Vuong's (1989) likelihood ratio test for model selection. A significant positive *Z*-statistic indicates that the first model is rejected in favor of the second model.

One important finding is that the superior predictive ability of *CFO* (model (2)) to *EARN* (model (1)) is greater for firms in the Energy and Materials groups than those in other industry categories. In these industry sectors, the variance proportion of Theil's *U*-statistic is higher than the bias and covariance proportions for model (1). This leads to the conclusion that *EARN* is not a relevant predictor of future cash flows in the Energy and Materials sectors. Instead, *CFO* is more informative and plays a more important role in forecasting future cash flows in these two industry groups. Another striking finding is that for firms in the Information Technology group, both model (1) and model (2) have the lowest adjusted R^2s and the highest *U*-statistics. In addition, a closer look at the results of out-of-sample forecasting tests reveals that the covariance proportion is lower than the variance and bias proportion for firms in the Health Care and Information Technology groups. These results suggest that the predictive abilities of both *EARN* and CFO are lowest in the Health Care group and Information Technology group.

These variations across industry sectors in the predictabilities of accrual- and cash-based accounting measures may be explained by prior research. For example, due to the complicated nature of the extractive industries (e.g., oil, gas, and mining), Wise and Spear (2000) argue that traditional cost-based accounting is potentially inadequate in evaluating the financial performance of these companies. Furthermore, firms within this industry adopt various accounting choices to measure preproduction costs and mineral reserves. Wise and Spear (2000, p.30)conclude that "[i]n spite of the importance of these industries to Australia's economy, the accounting for preproduction costs and mineral reserves and the disclosure practices of Australian extractive firms can at best be described as inadequate and might reasonably be referred to as an outstanding example of accounting flexibility." Quirin and Lawrence (1999) provide evidence that financial analysts heavily employ cash flow from operations rather than earnings for valuation decisions within the oil and gas industry. Defond and Hung (2003) argue that in industries with a high degree of heterogeneity in accounting method choices, such as the oil and gas industry, cash flow from operations is a more useful tool for measuring a firm's performance than earnings. This is because cash flow from operations is not influenced by discretionary accounting choices. Given that many companies in the Energy and Materials categories engage in the exploration and production of oil, gas, metals, and minerals, this explains the reason why the dominance of *CFO* over *EARN* in the Energy and the Materials categories is greater.

The general low predictive ability of both *EARN* and *CFO* for future cash flows in the Health Care and Information Technology categories may be explained by the attributes of accounting information in these two sectors: both encompass fast-changing and high technology-based companies such as software, hardware, biotechnology, and pharmaceuticals manufacturers. These companies are also regarded as "high technology" or "new economy" firms, which typically invest heavily in intangibles that can be directly expensed or arbitrarily amortised (Amir and Lev, 1996). Accordingly, key accounting variables, in particular earnings, are often greatly depressed and thus fail to convey useful information to its users regarding their predictive ability for future cash flows (e.g., Francis and Schipper, 1999; Amir and Lev, 1996). Evidence provided in previous price-based research supports the above argument and is in line with the findings of this study. For example, Amir and Lev (1996) find that earnings, cash flow from operations, and book values are not significantly or positively related to stock returns for firms in the cellular phone and biotechnology industries. Instead, nonfinancial indicators, such as total population in the licensed service area (as an indicator of potential growth) and the number of subscribers, are highly relevant to stock returns. However, financial information is value relevant when combined with nonfinancial information. Similarly, Trueman et al. (2000) document that the association between net income and market prices for internet stocks is irrelevant.

5. Further Analysis

Variations in the relative predictive ability of accrual-based and cash-based data across various industries may also be attributed to differences in the length of the operating cash cycle. This is because the length and components (i.e., days receivables, days inventory, and days payables) of the operating cash cycle are strongly related to industry factors (White et al. 2003). In this regard, Dechow

(1994, p. 31) concludes that earnings is a better indicator of a firm's performance than cash flow from operations for firms in industries with long operating cash cycles. This provides impetus to further examine whether the differences in the length of the operating cash cycle across industries can explain industry variations in the relative relevance of cash-based versus accrual-based measures in predicting future cash flows in the Australian capital markets. As per Dechow (1994),[4] the operating cash cycle is calculated as follows:

$$\text{Operating Cash Cycle} = \left(\frac{AR_t}{Sales/365}\right) + \left(\frac{INV_t}{Sales/365}\right) - \left(\frac{AP_t}{Sales/365}\right)$$

where AR_t is accounts receivable in year t, INV_t is inventory in year t, and AP_t is accounts payable in year t. The first ratio of the above equation (days receivables) determines the number of days until account receivables are converted to cash. The second ratio (days inventory) determines the number of days it takes to sell inventory. The third ratio (days payables) determines the number of days it takes to pay to trade creditors.

Using the *Aspect Financial Analysis* database, a total of 3,113 firm-year observations are available for the analysis. Table 4 presents descriptive statistics for the length of the operating cash cycle in total and by industry sector. Firms in the Energy, Materials, Information Technology, and Health Care sectors have negative mean values for operating cash cycles, while those in the Industrials, Consumer Discretionary, and Consumer Staples sectors have positive mean values. The median values of operating cash cycles across all industry sectors are positive, with the exception of the Energy sector. The high standard deviation at each industry sector and for the total sample of 3,113 firm-years indicates that there are substantial variations in the length of operating cash cycles within industries and across firms.

Table 4: Descriptive Statistics on the Length of the Operating Cash Cycle at Industry Level (Total Sample of 3113 Firm-Year Observations, 1992–2004)

Industry sectors	**The length of the operating cash cycle**		
	Mean	**Median**	**Standard deviation**
Energy	-126.62	-14.93	328.52
Materials	-70.29	13.67	322.32
Industrials	24.82	35.84	112.02
Consumer Discretionary	24.52	32.32	150.21
Consumer Staples	50.37	29.65	113.65
Health Care	-28.92	28.15	266.93
Information Technology	-11.53	34.96	289.04
Total Sample	**-12.02**	**21.16**	**345.46**

Operating cash cycles are estimated as the days accounts receivable plus days inventory minus days accounts payable.

To examine the effect of the length of operating cash cycle on the relative predictive ability of earnings and cash flow from operations at the industry level, the approach used in Dechow (1994) is adopted. Under this approach, the explanatory powers of *CFO* (model (2)) and *EARN* (model (1)) are estimated via industry-specific regressions (the adjusted R^2 values reported in Panel A of Table 3). The correlations between the adjusted R^2s of each model and the related mean operating cash cycles are then calculated. Table 5 presents the Spearman correlation coefficients. Consistent with Dechow (1994), there is a significant and negative correlation (-0.56) between operating cash cycles and the adjusted R^2s from seven industry-specific *CFO* regressions (model (2)). In contrast, the explanatory power of the *EARN* regression model (model (1)) at industry level is significantly and positively correlated to operating cash cycles (0.38). These again confirm that the predictive ability of *CFO* (*EARN*) increases as the length of the operating cash cycle decreases (increases). Furthermore, these

[4] This formula is slightly different from Dechow (1994), as she uses average accounts receivable, inventory, and accounts payable in the calculation.

results indicate that variations in the length of the operating cash cycle among industries can explain, at least partially, differential predictabilities of earnings and cash flow from operations across industries.

Table 5: Spearman Correlation between the Adjusted R^2s from Seven Industry-Specific Regressions of Current Cash Flow from Operations on One-Year Lagged Earnings (Model (1)) or One-Year Lagged Cash Flow from Operations (Model (2)) and the Average Industry Operating Cash Cycle

	Operating Cash Cycle
Adjusted R^2 from earnings regressions	0.38†
Adjusted R^2 from cash flow regressions	-0.58†

† Significant at the 0.01 level.

6. Conclusion

This paper re-examines the relationship between earnings, cash flow from operations, and future cash flows, focusing on the role of industry. To test this issue, Australian data is employed for the sample period of 1992-2004. The cash flow from operations figures used in this study are reported under the cash flow statement. To assess the predictive ability of the forecasting models, within-sample and out-of-sample forecasting tests are applied across seven industry sectors. The findings of this study indicate that both aggregate earnings and cash flow from operations are relevant in predicting future cash flows in the Australian context. This study also provides corroborating evidence of the superior forecasting ability of actual cash flow from operations over accrual earnings, but demonstrates that there are systematic industry differences in the relation between earnings, cash flow from operations, and future cash flows. In particular, the results show that earnings are a poor predictor of future cash flows in the Energy and Materials groups, while cash flow from operations play an important role in improving the forecast of future cash flows in these industry groups. In addition, both cash flow from operations and earnings have a weak relationship with future cash flows in the Health Care and Information Technology sectors. This study has two limitations. First, the models used in this study use one-year lag data to predict current cash flows. Therefore, the results may not be generalizable over a longer prediction period. Second, the empirical evidence of this study may be influenced by survivorship bias.

References

[1] Amir, E. And B. Lev, 1996. "Value-Relevance of Nonfinancial Information: the Wireless Communications Industry", *Journal of Accounting and Economics* 22, pp. 3-30.

[2] Austin, L.M. and M. E. Bradbury, 1995. "The Accuracy of Cash Flow Estimation Procedures", *Accounting and Finance*. 35, pp. 73-86.

[3] Australian Accounting Standards Board (AASB), 1991. "Accounting Standard AASB 1026: Statement of Cash Flows", *Australian Accounting Standards Board*, Melbourne, Vic.

[4] Australian Accounting Standards Board (AASB), 1997. "Accounting Standard AASB 1026: Statement of cash flows",*Australian Accounting Standards Board*, Melbourne, Vic.

[5] Australian Accounting Standards Board (AASB), 2004. "AASB 107: Cash Flow Statements", *Australian Accounting Standards Board*, Melbourne, Vic.

[6] Ball, R., S.P. Kothari, and A. Robin, 2000. "The Effect of International Institutional Factors on Properties of Accounting Earnings", *Journal of Accounting and Economics* 29, pp. 1-51.

[7] Barth, M.E., W.H. Beaver, J.R.M. Hand, and W.R. Landsman, 2005. "Accruals, Accounting-Based Valuation Models, and the Prediction of Equity Values", *Journal of Accounting, Auditing & Finance* 20, pp. 311-345.

[8] Barth, M.E., D.P. Cram, and K.K. Nelson, 2001. "Accruals and the Prediction of Future Cash Flows", *The Accounting Review* 76, pp. 27-58.

[9] Bartov, E., S. Goldberg, and M.S. Kim, 2001. "The Valuation Relevance of Earnings and Cash Flows: an International Perspective',*Journal of International Financial Management and Accounting* 12, pp. 103-132.

[10] Bowen, R.M., D. Burgstahler, and A.D. Lane, 1986. "Evidence on the Relationships between Earnings and Various Measures of Cash Flow", *The Accounting Review* 61, pp. 713-725.

[11] Cheng, C.S.A. and S.S.M. Yang, 2003. "The Incremental Information Content of Earnings and Cash Flows from Operations Affected by Their Extremity", *Journal of Business Finance and Accounting* 30 (1-2), pp. 73-116.

[12] Clinch, G.J., B.K.K. Sidhu, and S. Sin, 2002. "The Usefulness of Direct and Indirect Cash Flow Disclosures", *Review of Accounting Studies* 7, pp. 383-404.

[13] DeAngelo, L., 1986. "Accounting Numbers as Market Valuation Substitutes: A Study of Management Buyouts of Public Stockholders", *The Accounting Review* 61, pp. 400-420.

[14] Dechow, P.M., 1994. "Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals", *Journal of Accounting and Economics* 18, pp. 3-42.

[15] Dechow, P.M., S.P. Kothari, and R.L. Watts, 1998. "The Relation between Earnings and Cash Flows", *Journal of Accounting and Economics* 25, pp. 133-168.

[16] DeFond, M.L. and M. Hung, 2003. "An Empirical Analysis of Analysts' Cash Flow Forecasts", *Journal of Accounting and Economics* 35, pp. 73-100.

[17] Farshadfar, S., C. Ng, M. Brimble, 2008. "The Relative Ability of Earnings and Cash Flow Data in Forecasting Future Cash Flows: Some Australian Evidence", *Pacific Accounting Review* 20, pp. 254-268.

[18] Financial Accounting Standards Board, 1978. "Statement of Financial Accounting Concepts 1: Objectives of Financial Reporting by Business Enterprises", *Financial Accounting Standards Board*, Stamford, CT.

[19] Francis, J. and K. Schipper, 1999. "Have Financial Statements Lost Their Relevance?" *Journal of Accounting Research* 37, pp. 319-332.

[20] Greenberg, R.R., G.L. Johnson, and K. Ramesh, 1986. "Earnings versus Cash Flows as a Predictor of Future Cash Flow Measures", *Journal of Accounting, Auditing and Finance* 1, pp. 266-277.

[21] Gu, Z., C.W.J. Lee, and J.G. Rosett, 2005. "What Determines the Variability of Accounting Accruals?",*Review of Quantitative Finance and Accounting* 24, pp. 313-334.

[22] Healy, P.M., 1985. "The Effect of Bonus Schemes on Accounting Decisions", *Journal of Accounting and Economics* 7, pp. 85-107.

[23] Habib, A., 2010. "Prediction of Operating Cash Flows: Further Evidence from Australia", Australian Accounting Review, 20, pp. 134-143.

[24] Hribar, P. and D. Collins, 2002. "Errors in Estimating Accruals: Implications for Empirical Research", *Journal of Accounting Research* 40, pp. 105-134.

[25] International Accounting Standards Committee (IASC), 1992. "International Accounting Standard 7: Cash flow Statements", *International Accounting Standards Committee*,London.

[26] Kim, M., and W. Kross, 2005. "The Ability of Earnings to Predict Future Operating Cash Flows Has Been Increasing—Not Decreasing", *Journal of Accounting Research* 43, pp. 753-780.

[27] Percy, M. and D.J. Stokes, 1992. "Further Evidence on Empirical Relationships between Earnings and Cash Flows", *Accounting and Finance* 32, pp. 27-49.

[28] Pindyck, R.S. and D.L. Rubinfeld, 1998. "Econometric Models and Economic Forecasts", *McGraw-Hill*, New York, NY.

[29] Quirin, J.J. and Lawrence, 1999. "Fundamental Information Analysis in the Oil and Gas Industry: Key Analysts Share Their Opinions', *Oil, Gas and Energy Quarterly* 47, pp. 843-865.

[30] Subramanyam, K.R. and M. Venkatachalam, 2007. "Earnings, Cash Flows, and *Ex Post* Intrinsic Value of Equity', *The Accounting Review* 82, pp. 457-481.

[31] Trueman, B., F. Wong and X. Zhang, 2000. “The Eyeballs Have It: Searching for the Value in Internet Stocks”, *Journal of Accounting Research* 38(3), pp. 137-162.

[32] Watts, R.L. and R.W. Leftwich, 1977. “The Time Series of Annual Accounting Earnings”, *Journal of Accounting Research* 15, pp. 253-271.

[33] Wise, T. and N. Spear, 2000. “Accounting for Extractive Industries: an Australian Perspective”, *Petroleum Accounting and Financial Management* 19, pp. 30-53.

[34] White, G.I., A.C. Sondhi, and D. Fried, 2003. “The Analysis and Use of Financial Statements”, 3rd edition, *John Wiley & Sons*, Hoboken, New Jersey.

[35] White, H., 1980. “A Heteroskedasticisity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasiticy”, *Econometrica* 48, pp. 817-838.

[36] Vuong, Q.H., 1989. “Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses”, *Econometrica*57, pp. 307-334.