Further Evidence on the Usefulness of Direct Method Cash Flow Components for Forecasting Future Cash Flows

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Further evidence on the usefulness of direct method cash flow components for forecasting future cash flows

The International Journal of Accounting **(forthcoming)**

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Abstract

Based on pre-IFRS data from Australia, we provide further evidence that disaggregating operating cash flow into its components enhances the predictive ability of aggregate operating cash flow in forecasting future cash flows. We also find that cash received from customers and cash paid to suppliers and employees complement each other in enhancing the overall predictive ability of cash flow components. The results are robust to a battery of sensitivity tests, including control for industry membership, firm size, profitability, negative cash flows, and the length of the operating cash cycle. Our results contribute to the policy debate as to whether reporting of the direct method cash flow statement should be mandatory.

JEL classification: M41

Keywords: Cash flow; Cash flow components; Forecasting future cash flows; Direct method; Indirect method.

1. Introduction

The forecasting of future cash flows is fundamental to a firm's valuation and investment analysis (e.g., Krishnan & Largay, 2000). The Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) observe that providing information to help financial statement users forecast a firm's future cash flows is one of the prime objectives of financial reporting (see FASB, 1978; International Financial Reporting Standards [IFRS] Foundation, 2010a). Moreover, the current joint project of the IASB and the FASB, the 'Financial Statement Presentation', proposes to mandate disaggregated operating cash flow reporting under the direct method.[1] The standard setters claim that the direct method cash flow components are better than aggregate operating cash flow in predicting a firm's future cash flows (see International Accounting Standards Committee [IASC], 1992, para. 19; FASB, 1987, para. 107). While a few studies have investigated this claim (e.g., Krishnan & Largay, 2000; Cheng & Hollie, 2008; Orpurt & Zang, 2009), the studies have been mostly confined to U.S. firms.

The U.S. studies on the usefulness of the direct method cash flow components suffered from two problems. First, the direct method cash flow data were mostly unavailable in the U.S. due to the predominance of the indirect method. Hence, cash flow components had to be estimated. This resulted in data estimation errors (Bradbury, 2011; Krishnan & Largay, 2000; Orpurt & Zang, 2009). Moreover, the U.S. studies suffered from self-selection bias (Bradbury, 2011) due to the voluntary adoption of the direct method by some of the US firms. Thus, a lack of comprehensive evidence on the merit of the direct method cash flow statement creates an opportunity for further research.

[1] See S28 and S30 of *Financial Statement Presentation – Introduction to Staff Draft of an Exposure Draft* (IFRS Foundation, 2010b) and paragraphs 170, 172, 177, 178 of *Staff Draft of an Exposure Draft on Financial Statement Presentation* (FASB, 2010).

Australian firms have been required to present cash flow statements using the direct method since 1992.[2,3] We link actual direct cash flow components with actual future cash flows to investigate the following research question: Do cash flow components, as reported in the direct method, have a greater ability to predict future cash flows than aggregate operating cash flow? Using pre-IFRS data, we provide further evidence on the superior ability of the direct method operating cash flow components over aggregate operating cash flow for forecasting future cash flows. We also identify the source of this superior ability. We find that cash received from customers and cash paid to suppliers and employees complement each other in enhancing the overall predictive ability of cash flow components.

We divide our total sample period into a within-sample period (1992–2001) and an out-of-sample period (2002–2004). To evaluate the performance of the forecasting models, we first measure the explanatory powers of our models by the adjusted R^2 over the period 1992 to 2001. We then examine the forecast accuracy of the models by estimating Theil's *U*-statistic and its proportions over the period 2002 to 2004. We use the random-effects method, a panel data estimation technique, to estimate our regression models. We find that the predictive ability of both aggregated and disaggregated cash flow increases with firm size. Our results are consistent when we control for industry membership, the length of operating cash cycle, firm profitability, and the sign of operating cash flow. Our results are also robust when we increase the forecasting horizon from one year to four years.

[2] Wallace, Choudhury, and Pendlebury (1997) reported that Australia and New Zealand were the only two countries that mandated reporting the direct method cash flow statements. China was added to this list in 1998.
[3] Australia adopted the IFRS issued by the IASB as of January 1, 2005. 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 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 International Accounting Standard 7 (IASC, 1992).

We make a single but significant contribution to the literature on cash flow forecasting. We provide direct evidence, using actual cash flow data, that operating cash receipts and cash payments together are superior to net operating cash flow in the forecast of future cash flows. However, unlike the U.S. studies, our study does not suffer from data estimation errors and self-selection bias (see Bradbury, 2011). Thus, our results provide additional support for the usefulness of the direct method cash flow components and contribute directly to the global debate on whether direct method cash flow reporting should be preferred over the indirect method.

The remainder of the paper is organized as follows. Section 2 outlines the background for this study. Section 3 reviews the literature on the usefulness of the direct method cash flow information. Section 4 develops the research design. Section 5 describes the sample selection procedure and reports descriptive statistics. Section 6 discusses the main results. Section 7 provides results from various sensitivity analyses. Section 8 briefly summarizes the results and concludes the paper.

2. Background

Cash flows can be presented via two methods: direct and indirect. Under the direct method, major classes of gross operating cash inflows and outflows are reported. The commonly reported direct method cash flow components are cash receipts from customers, cash payments to suppliers and employees, payments for other operating expenses, interest received and paid, and taxes paid. These cash flow components may be extracted directly from the accounting system or determined indirectly by adjusting revenues, expenses, and other items in the income statement for changes in inventory, operating receivables and payables, other non-cash items, and cash-effects related to investing or financing activities (IASC, 1992, para. 19). Under the indirect method, only net operating cash flow is reported after adjusting net income for non-cash items and changes in current accruals. For external reporting, both the FASB and the IASB allow the use of either approach, although both the regulators prefer the direct method (FASB, 1987, para. 119; IASC, 1992, para. 19). The results of several survey-based studies also indicate greater support for the direct method from various user groups such as investors, financial analysts, loan officers, college professors, and managers (e.g., Jones, Romano, & Smyrnios, 1995; Jones & Ratnatunga, 1997; McEnroe, 1996; Jones & Widjaja, 1998; Chartered Financial Analyst [CFA] Institute, 2009).[4]

In practice, however, the vast majority of companies (approximately 97% to 98%) in the U.S. and other countries prepare their reports using the indirect method (e.g., Krishnan & Largay, 2000; Orpurt & Zang, 2009; Clinch, Sidhu, & Sin, 2002). The popularity of the indirect method among financial statement preparers stems from the perception that the direct method is complicated and unduly burdensome in terms of data collection and accounting systems design. This argument in opposition to the direct method has received criticism, however. For example, Bahnson, Miller, and Budge (1996) argue that the calculation and presentation of indirect cash flow statements are also not straightforward due to the articulation problem.[5] They conclude that the cost of reporting indirect method cash flow statements may be equal to, or greater than, the cost of reporting direct method cash flow statements. Furthermore, empirical research (e.g., Krishnan & Largay, 2000; Clinch et al., 2002; Orpurt & Zang, 2009) indicates that the direct cash flow figures estimated via either the indirect method or the balance sheet and income statement are subject to major measurement errors.

[4] For example, Jones and Widjaja (1998) found that a majority of respondents to their surveys believed that the direct method presents advantages in helping users understand cash flow data, facilitating cash flow analyses, and indicating company solvency, in addition to having a sounder conceptual basis and reflecting accepted commercial practice.

[5] Non-articulation occurs when changes in current assets and liabilities, as presented in cash flow statements under the indirect method, are not equal to changes reflected on the comparative balance sheets (Bahnson et al., 1996).

The strong appeals for the direct method and the inherent difficulty of estimating the direct cash flows by external users have led various user groups to call for the mandatory adoption of the direct method (e.g., Wallace et al., 1997; CFA Institute, 2007). As discussed in Section 1, the FASB and the IASB's joint project, the 'Financial Statement Presentation', recently proposed the mandatory reporting of the direct method cash flow statement on the grounds of improved cash flow forecasting (FASB, 2010, paras. 170, 172, 177, 178; IFRS Foundation, 2010b, S28 and S30). We investigate whether this is indeed the case using actual cash flow components data from Australia.

3. Prior research

3.1. The relationship of direct method cash flow information with future cash flows

The literature on the usefulness of the direct method cash flow components in the forecast of future cash flows is sparse. However, Bradbury (2011) provides a thorough discussion on the current state of cash flow forecasting literature. Hence, we discuss only some of the key studies in this area.

Krishnan and Largay (2000) were the first to examine this topic using a small sample of 405 firm-year observations in the U.S. context. They report that (1) direct method cash flow components have an incremental predictive ability beyond aggregate operating cash flows; (2) estimated direct method cash flow components have greater predictive ability than the set of earnings, receivables, payables, and inventory; and (3) estimated direct method cash flow components contain significant measurement errors.

Cheng and Hollie (2008) and Orpurt and Zang (2009) conducted two other U.S. studies that provide evidence of the higher predictive ability of estimated direct method cash flow disclosures for future cash flows compared to that of aggregate operating cash flow. Cheng and Hollie (2008) further indicate that the estimated direct method cash flow components provide incremental information over and above accrual components. Orpurt and Zang's (2009) results show that calculating direct method cash flow information via indirect method cash flow components leads to severe articulation errors.

3.2. Relationship of direct method cash flow information with stock returns and future earnings

Only a few studies investigate the usefulness of the direct method cash flow information in explaining stock returns and future earnings. Using US data, Livnat and Zarowin (1990) find that estimated direct method cash flow information is positively related to stock returns (except for tax payments). Using Australian data, Clinch et al. (2002) find that the direct method cash flow components have incremental ability beyond aggregate operating cash flow in explaining stock returns for the mining industry only. Orpurt and Zang (2009) attempt to extend Clinch et al. (2002) by providing evidence that the direct method cash flow statements enable current stock returns to better reflect information about future earnings and cash flows. Orpurt and Zang also provide evidence for the superior ability of disaggregated operating cash flow over aggregated operating cash flow in the forecast of future earnings. A similar conclusion is drawn for the relationship between the direct method cash flow components and future earnings in an Australian context, as documented by Arthur, Cheng, and Czernkowski (2010). Our research complements the above studies by directly using future cash flows instead of using stock returns or future earnings to evaluate the usefulness of direct method cash flow components.

4. Research design

To test our research question, we estimate the following linear regression models:

$$CF_{it} = \alpha_0 + \alpha_1 CF_{it-j} + \varepsilon_{it} \quad (1)$$

$$\begin{aligned} CF_{it} = {} & \beta_0 + \beta_1 CSHRD_{it-j} + \beta_2 CSHPD_{it-j} + \beta_3 INTPD_{it-j} + \beta_4 TXPD_{it-j} + \\ & \beta_5 OTHCSH_{it-j} + \varepsilon_{it} \end{aligned} \quad (2)$$

where i and t denote firm and year, and j ranges from 1 to 4; *CF* is the net cash flow from operations; *CSHRD* is the cash received from customers; *CSHPD* is the cash paid to suppliers and employees; *INTPD* is the net interest paid (the difference between the interest paid and interest received); *TXPD* represents the taxes paid; and *OTHCSH* represents other cash flows from operations (i.e., $OTHCSH = CF - (CSHRD - CSHPD - INTPD - TXPD)$).

Note that no standard classification of operating cash inflows and outflows exists either in the research literature or in accounting standards (see Wallace et al., 1997). We identify cash received from customers, cash paid to suppliers and employees, net interest paid, and taxes paid as the main direct method cash flow components. We do this for three reasons. First, these items have been consistently listed as examples of cash flows from operating activities by accounting regulators (e.g., AASB, revised 1997, Appendix 1; FASB, 1987, paras. 22–23, IASC, 1992, Illustrative Example section). Second, the classification is consistent with that employed by Clinch et al. (2002) and Orpurt and Zang (2009), which may increase the comparability of our results.[6, 7] Third, the data for these items are available in the *Aspect Financial Analysis* database for our sample years.

The dataset used for this study is panel data. Based on Taylor's (1980) guidance and the results of the Hausman (1978) test, we use the time random-effects method to estimate our regression models. This panel data analysis technique considers a random error component to control for cash flow variation over time (see Gujarati, 2003).[8, 9] In addition, following Petersen

[6] The direct method cash flow components used in other related studies are slightly different. For example, Krishnan and Largay (2000) use interest paid and interest received rather than net interest paid, but they do not include other operating cash flows in their prediction models. Arthur et al. (2010) and Cheng and Hollie (2008) include dividends received and operating expenses, respectively, as separate items in their cash flow classification.

[7] We also estimate model (2) based on an alternative set of direct cash flow components, that is, cash received from customers, cash paid to suppliers and employees, interest received, interest paid, taxes paid, dividends received, and other cash flows. Our conclusions are not altered.

[8] There is another well-recognized estimation method relating to panel data analysis known as the fixed-effects method. We consider a random-effects model rather than the fixed-effects model for two reasons: first, Taylor (1980) documents that a random-effects model is more appropriate than a fixed-effects model if $T>3$ and $(N-K)>9$,

(2009), all regression models are estimated with standard errors clustered by firm to control for heteroscedasticity and possible residual dependence.[10]

To assess whether past direct cash flow components capture distinct information about current operating cash flows, we test for the equality of coefficients across the cash flow components using the chi-squared test (hereafter, χ^2 test). This approach is consistent with Clinch et al. (2002) and Orpurt and Zang (2009). To evaluate the forecasting performance of the models, we first compare the adjusted R^2 of models (1) and (2) for the period 1992 to 2001.[11] The value of this within-sample goodness of fit measure implies the extent to which a model can explain the total variation of future cash flows. We augment the reliability of our within-sample forecasting results by conducting out-of-sample forecasting tests. We follow this approach because a higher adjusted R^2 does not necessarily mean a superior predictive ability (Watts & Leftwich, 1977). Hence, following Kim and Kross (2005) and Bandyopadhyay, Chen, Huang, and Jha (2010), we estimate Theil's *U*-statistic. It is a measure of forecast error that shows how accurately the forecasted cash flow matches with its actual future value in the hold-out sample (2002–2004). The *U*-statistic is computed as follows:

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(F_{it} - Y_{it})}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(F_{it})^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_{it})^2}} \tag{3}$$

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where T is the number of time-series data, N is the number of cross-sectional units, and K is the number of regressors. Our sample specifications meet the conditions. Second, to choose between these two methods, Hausman's (1978) test can be used (see Greene, 2000; Gujarati, 2003). The results of the Hausman test (unreported) verify the appropriateness of the use of the random-effects model in our study.

[9] We also perform firm random-effects regression models to take into account firm-specific differences. Given that the results are qualitatively similar, for the sake of parsimony, we only report the results of time random effects. Furthermore, as discussed in Section 7, we divide our sample firms into more homogeneous groups based on a number of important firm characteristics to further take into account firm-specific effects in our analysis.

[10] See Petersen (2009) for further details on the application of clustered standard errors in panel data sets.

[11] We estimate our regression models using data for the entire period of 1992 to 2004. We also re-estimate models 1 and 2 using one-year through four-year-ahead operating cash flows as the dependent variable and current aggregate operating cash flows or current direct cash flow components as the independent variables. The results are qualitatively similar.

where Y_{it} = the actual value of operating cash flows for firm i and time period t (t = 2002, 2003, 2004); F_{it} = the forecasted value of operating cash flows for firm i and time period t calculated based on the estimated coefficients from related models (i.e., model (1) or (2)); and T = number of periods.

An important feature of Theil's *U*-statistic as a measure of forecast error is that it is scale-invariant. Further, it can be decomposed into bias, variance, and covariance proportions. In a good forecast, the covariance proportion, which is indicative of unsystematic error, should be larger than the bias and variance proportions. The bias proportion reports systematic error and the variance proportion indicates the extent to which the fluctuations in the fitted series follow those in the actual series. The magnitude of Theil's *U*-statistic falls between zero, which indicates a perfect fit, and one, which indicates that the predictive ability of the model is at its worst (Pindyck & Rubinfeld, 1998).

5. Data

5.1. Sample selection

We obtain the relevant data from the *Aspect Financial Analysis* database for the companies listed on the Australian Securities Exchange (ASX). The sample period begins in 1992, the year the AASB first required Australian firms to report the direct method cash flow statement. The sample ends in 2004 to avoid any structural change in the data due to Australia's adoption of the IFRS to be put into effect beginning January 1, 2005. In our data, aggregated operating cash flow and direct method cash flow components are the actual numbers as reported in the cash flow statements. As in Krishnan and Largay (2000), the variables are scaled by the number of outstanding ordinary shares.

Firms in the Financials sector[12] are excluded because financial reporting in this sector is based on special accounting regulations. Further, we select only firms with data for all the variables over the entire sample period. This allows us to control for potential changes in sample characteristics over time due to the departure of some firms and the inclusion of new firms in the sample. This requirement also allows us to span the forecast horizon. The requirement for data continuity over the entire sample period likely introduces a survivorship bias in the sample in terms of the inclusion of larger and more successful firms. To alleviate this concern, in Section 5.2, we compare our sample with the entire population, the ASX market, to determine whether our sample is representative of the population as a whole.

Based on our sample requirements, the initial sample is 4,537 firm-years, representing 349 firms. When we exclude the outliers (17 observations), as diagnosed by Cook's distance, the sample size is reduced to 4,520 firm-year observations, representing 348 firms.[13] In Section 7.4, we further discuss the impact of potential outliers in the data.

5.2 Descriptive statistics

Table 1 compares the sample composition and the ASX market (the population) composition in terms of industry sectors and firm size. As reported in Panel A, based on the number of listed firms in each industry sector, the sample closely follows the sector composition of the ASX market. However, the sample under-represents the Information Technology sector (4.58% in our sample but 8.57% in the ASX market) and the Health Care sector (5.16% in our sample but 10.43% in the ASX market), and over-represents the Consumer Staples sector (6.88% in our

[12] Sector is the first level of industry classification in the Global Industry Classification Standard (GICS) system. GICS is a joint Standard & Poor's/Morgan Stanley Capital International product that seeks to standardize industry definitions (ASX, 2011). The GICS system is comprised of 10 economic sectors, 23 industry groupings, 59 industries, and 122 sub-industries.

[13] For more details on the merits of Cook's distance in diagnosing outliers, see Wilson (1997).

sample but 3.99% in the ASX market). This is potentially due to differential compliance levels with AASB 1026 (AASB, 1991) across firms in different industry categories.

TABLE 1 ABOUT HERE

In Panel B of Table 1, we compare the sample firms with the ASX market for each year using the mean and median values of total assets as a proxy for firm size. Although the mean total assets of our sample firms is larger than that of the ASX market in each sample year, such differences are not statistically significant at conventional levels. However, the Mann-Whitney *U*-test suggests that the median firm in our sample is significantly larger than the ASX median firm in 2002, 2003, and 2004. When we perform a similar analysis (untabulated) using market capitalization, we find a significant difference between the means for 2000 to 2004 but no significant difference between the medians in any sample year. Overall, there is some evidence that our sample firms are larger (and potentially more successful) than the typical firms in the ASX market; however, the representativeness of our sample is not severely compromised.

Panel A of Table 2 reports sample characteristics based on market capitalization and total assets. Our sample firms had a mean (median, standard deviation) market capitalization and a mean (median, standard deviation) total assets of $1,778.47 ($19.25, $2,156.26) million and $782.88 ($19.68, $4,642.8) million, respectively.[14] Clearly, the means are much smaller than the respective standard deviations. This suggests a substantial variation with respect to firm size within the sample, indicating that our sample is not dominated by large firms. Our sample, however, contains a small number of very large firms, as indicated by a larger mean compared to

[14] All financial figures in this paper are in Australian dollars unless otherwise specified.

the median in each measure. These sample characteristics are consistent with Clinch et al. (2002).[15]

Panel B of Table 2 reports the descriptive statistics for the cash flow variables. The mean (median, standard deviation) of *CSHRD* and *CSHPD* is \$2.57 (\$0.15, \$6.53) and \$2.34 (\$0.14, \$6.23) per ordinary share, respectively. These are much larger than the respective values for *INTPD*, *TXPD*, and *OTHCSH*. Thus, the explanatory power of *CF* is considerably influenced by *CSHRD* and *CSHPD*. Panel C of Table 2 presents Pearson correlation coefficients for the non-signed cash flow variables. *CF* is significantly positively correlated with *CSHRD* (r = 0.44), *CSHPD* (r = 0.40), *INTPD* (r = 0.11), *TXPD* (r = 0.58), and *OTHCSH* (r = 0.37) at the 0.01 level. With the exception of *OTHCSH* and *CSHPD*, *CF* components are significantly related to each other. The correlation between *CSHRD* and *CSHPD* is 0.99 (significant at the 0.01 level). This strong association is expected because of the dependence of cash outflows on the amount of cash inflows; however, severe multicollinearity may exist in regression model (2). We address this issue in our sensitivity tests in Section 7.3.

TABLE 2 ABOUT HERE

6. Empirical results

Panel A of Table 3 presents the results of estimating models (1) and (2) using the time random-effects method for the within-sample period of 1992 to 2001. Model (2), with an adjusted R^2 of 55%, has higher overall explanatory power than model (1) (adjusted R^2 = 53%). The χ^2 statistic of 18.02 indicates that the coefficient estimates on direct method cash flow components significantly differ from each other at the 0.01 level. Moreover, in model (1), the net operating cash flow (*CF* = 0.76, *t*-statistic = 15.63) is positively and significantly related to

[15]The median values for market capitalization and total assets in Clinch et al. (2002) are relatively larger than those reported in this paper. This, however, is expected as their sample is restricted to companies with market values exceeding \$10 million.

future cash flows at the 0.01 level. The slope coefficients for cash received from customers (*CSHRD* = 0.64, *t*-statistic = 9.26), cash paid to suppliers and employees (*CSHPD* = -0.63, *t*-statistic = -9.08), net interest paid (*INTPD* = -0.45, *t*-statistic = -2.89), and other cash flows from operations (*OTHCSH* = 0.71, *t*-statistic = 11.93) in model (2) carry the expected signs and are statistically significant at the 0.01 level. However, the coefficient for taxes paid (*TXPD* = 0.01, *t*-statistic=0.02) is not significant at conventional levels.

Panel A of Table 3 reveals that *CSHRD* and *CSHPD* have higher persistence than *INTPD* and *TXPD*, as shown by the magnitudes of their slope coefficients. This high persistence of *CSHRD* and *CSHPD* is consistent with the argument that they are more closely related to a firm's income-producing and core operating activities compared to *INTPD* and *TXPD* (Cheng & Hollie, 2008). In particular, *INTPD* is primarily linked to investing and/or financing activities as opposed to core operating activities (Wallace et al., 1997). The low persistence of *TXPD* may be attributed to the fact that the item is a mix of operating and non-operating cash outflows. In particular, it would be impractical for firms to separate *TXPD* arising from operating, investing, and financing activities in the cash flow statement. The item may also be related to taxable income in a different financial year (AASB, revised 1997, para. 7.2.1; IASC, 1992, para. 36). These characteristics may weaken the relationship between *TXPD* and future cash flows. The high persistence of *OTHCSH* is difficult to explain as it is influenced by the predictive values of a wide range of remaining operating cash flow disclosures. However, this variable is of less interest in this study as it is seen as a residual number only.

The results of within-sample tests for models (1) and (2) with longer lag periods are reported in Panels B (two-year lag), C (three-year lag), and D (four-year lag) of Table 3. These results consistently show two patterns. First, model (2) consistently outperforms model (1). That is, the direct method cash flow components individually contribute to future cash flow predictions, while using aggregate operating cash flows alone masks their information content. Second, although the explanatory power of each model decays as the forecast horizon increases, the difference in explanatory powers between the two models widens as the forecast horizon increases.

TABLE 3 ABOUT HERE

We can draw similar conclusions from the out-of-sample (2002–2004) forecasting tests, as summarised in Panel E of Table 3. A considerably higher covariance proportion than the bias and variance proportions suggests that both models (1) and (2) are able to reliably predict future cash flows. The value of Theil's *U*-statistic for model (2) with a single lag (one year) is 0.33. This is lower than the value for model (1), which is 0.36. This result indicates that the predictive power of model (2) for future cash flows is higher than that of model (1). This conclusion remains unchanged when the lag length is increased from one to four years.

Overall, both within-sample and out-of-sample forecasting results robustly affirm that both aggregate operating cash flow and direct method cash flow components are useful in predicting future cash flows. However, the direct method cash flow components have superior predictive ability relative to that of aggregate operating cash flow reported under the indirect method.

7. Additional analyses and robustness checks

7.1. Industry membership

The relative importance of historical cash flow data in the forecast of future cash flows is likely to be different across industries. This is because firms' economic conditions and adopted accounting policies are generally similar within an industry (e.g., Barth, Cram, & Nelson, 2001; Barth, Beaver, Hand, & Landsman, 2005; Dechow, 1994). Thus, to understand the role of industry membership on the predictive ability of direct method cash flow components, we re-estimate our cash flow prediction models after grouping firms by industry sectors based on a two-digit GICS code.[16, 17] These results are reported in Table 4. Our sample firms did not change their industry sectors during the entire sample period. However, the Telecommunication Services and Utilities sectors, with six and three firms, respectively, were excluded from our industry analysis.

TABLE 4 ABOUT HERE

Table 4 reports the results of estimating models (1) and (2) at the industry sector level. In Panel A, the slope coefficients on *CF* of model (1) are positive and significant at either the 0.01 or the 0.05 level in all industry sectors. In model (2), the slope coefficients on *CSHRD* and *CSHPD* have the predicted signs and are statistically significant at the 0.01 level in each industry sector except Information Technology. In Information Technology, only *CSHRD* is statistically significant at the 0.10 level. Although the sign and the significance of other cash flow components (*INTPD*, *TXPD*, and *OTHCSH*) vary across industry sectors, the adjusted R^2 of model (2) is higher than that of model (1) across all industries. In Panel B, the χ^2 tests on the equality of cash flow components are also rejected at conventional levels for all industry sectors.

In Panel C of Table 4, with the exception of model (1) for the Health Care sector, and models (1) and (2) for the Information Technology sector, the covariance proportions are higher than their bias and variance proportions for both models (1) and (2) across all industries. That is, past year aggregate operating cash flow cannot reliably predict current operating cash flow either in Health Care or in Information Technology. These results are consistent with Amir and Lev

[16] GICS was introduced to the Australian capital market as an industry classification scheme in June 2001. However, historical GICS codes are available for our sample firms over the period of 1992 **to** 2004 from the *Aspect Financial Analysis* database.

[17] Our analysis is based on a two-digit classification because of data limitation. Sample sizes for industry groupings drop significantly when a four- or six-digit classification is applied.

(1996) and Francis and Schipper (1999) who argue that key accounting variables, including cash flows, are often largely irrelevant to future cash flows in high technology firms.

7.2. Year-by-year regression analysis

Consistent with Barth et al. (2001) and Arthur et al. (2010), we re-estimated models (1) and (2) using OLS regression for each sample year as a further sensitivity test to control for possible autocorrelations in the disturbances. In addition, standard errors were clustered by firm. For brevity, Table 5 reports the results of one-year lag models only. The adjusted R^2 of model (2) is higher than that of model (1) across all sample years. The results in Table 5 generally confirm our primary conclusion that the direct method cash flow components enhance the forecast of future cash flows beyond the aggregate operating cash flow only.

TABLE 5 ABOUT HERE

7.3 Multicollinearity tests

We indicated in Section 5.2 that the coefficient of the correlation between *CSHRD* and *CSHPD* at 0.99 may pose a multicollinearity problem in model (2). One way to alleviate this potential problem is to exclude one of the highly collinear variables from the model. Accordingly, we modify model (2) to include only either *CSHRD* or *CSHPD*. These partial models are:

$$CF_{it} = \gamma_0 + \gamma_1 CSHRD_{it-1} + \gamma_2 INTPD_{it-1} + \gamma_3 TXPD_{it-1} + \gamma_4 OTHCSH_{it-1} + \varepsilon_{it} \quad (4)$$

$$CF_{it} = \delta_0 + \delta_1 CSHPD_{it-1} + \delta_2 INTPD_{it-1} + \delta_3 TXPD_{it-1} + \delta_4 OTHCSH_{it-1} + \varepsilon_{it} \quad (5)$$

The definitions of the variables are the same as in model (2).

Panel A of Table 6 reports the within-sample forecasting statistics for models (4) and (5). *CSHRD* and *CSHPD* are significant at the 0.05 level in their respective models. The χ^2 tests reject the null hypothesis of equality of coefficients at the 0.01 level. In addition, the adjusted R^2s of models (4) and (5) are 38% and 37%, respectively, which are significantly lower than that of model (2) at 55%. Thus, *CSHRD* and *CSHPD* in the same model (i.e., model (2)) play complementary roles to each other.

Theil's *U*-statistic of 0.33 in model (2) is less than that of 0.39 in model (4) and 0.40 in model (5), as reported in Panel B of Table 6. This confirms that *CSHRD* and *CSHPD* together have better predictive ability than using either *CSHRD* or *CSHPD* alone. These results remain qualitatively similar for other lags and after grouping firms based on industry membership, size, and profitability (untabulated).[18] We also re-examine our regression models after combining *CSHRD* and *CSHPD*, another common method of mitigating a multicollinearity problem (see Gujarati, 2003). However, combining these two variables does not alter our original results (untabulated).

In sum, we conclude that the forecast of future cash flows is superior when *CSHRD* and *CSHPD* are simultaneously present in the forecasting model relative to using *CSHRD* or *CSHPD* alone or combining them into one variable.

TABLE 6 ABOUT HERE

7.4. Additional sensitivity tests

Cheng and Hollie (2008) argue that the variability of accounting data may be conditional on firm size to the extent that size is correlated with a firm's risk and information environment. Accordingly, we examine the impact of size on our main results by dividing the sample firms

[18] Maddala (2001, p. 278) argues that multicollinearity is a significant problem for prediction purposes if the predictive value of the model (here, model (2)) is lower than that of a model with a subset of the independent variables (here, models (3) or (4)).

into two groups: Small and Large.[19] Untabulated results suggest that our main findings at the total sample level are unaffected by firm size. However, the predictive ability of both aggregated and disaggregated operating cash flow for future cash flows increases with firm size.

We also check the robustness of our results for the length of the operating cash cycle,[20] the profitability, and the negative operating cash flows.[21] Untabulated results suggest that our main conclusions drawn at the total sample level are not affected by incorporating these controls into our tests. However, the predictive ability of both aggregate operating cash flow and direct method cash flow components are noticeably higher when the length of the operating cash cycle is short, the firm is profitable, or the firm generates positive net operating cash flow.

Following Barth et al. (2001), we also find that our results are robust to using average total assets as an alternative deflator. Regarding outliers, we repeat our analysis by removing the observations in the extreme upper and lower 1% of aggregate operating cash flow, as in Cheng and Hollie (2008) and Orpurt and Zang (2009). We also remove the bottom and top 1% of cash received from customers and cash paid to suppliers and employees to ensure the results of model (2) are not driven by extreme values of these two variables. We find that our results are not influenced by their exclusion.

8. Summary and conclusion

[19] To classify firms by size, we adopt the procedure of Ismail and Choi (1996). First, all firms in the total sample are ranked based on their total assets at the end of the year at three different points in time: beginning (1992), middle (1998), and ending year (2004).[19] Then each of these three groups of firms is equally trichotomized. A firm is eliminated from the analysis if it does not demonstrate consistency in its group membership over the three points in time. Firms in the first and third strata are assigned to Small and Large groups, respectively.

[20] The operating cash cycle is calculated as the day's receivable ratio plus the day's inventory ratio minus the day's payable ratio. Consistent with Charitou (1997), the bottom and top 40% of the observations are ranked based on the length of the operating cash cycle and assigned to two groups: Short Operating Cash Cycle, comprised of observations with an operating cash cycle of less than nine days, and Long Operating Cash Cycle, comprised of observations with an operating cash cycle of more than 38 days. Dechow, Kothari, and Watts (1998) and Barth et al. (2001) divide their total sample based on operating cash cycle-quartiles. Untabulated findings indicate that this grouping does not alter our conclusions.

[21] To examine the effect of profitability (negative operating cash flows) on our prediction models, we divide the total sample into the groups Loss (Negative cash) and Profit (Positive cash), based on negative and positive earnings (operating cash flows).

We investigated whether the direct method operating cash flow components possess higher predictive ability for future cash flows over aggregate operating cash flow. We used data from Australia, where the reporting of the direct method cash flow components has been mandatory since 1992. Unlike prior U.S. studies in this area, our study does not suffer from self-selection bias and errors in estimating cash flow components.

We analyzed a sample of 348 firms between 1992 and 2004, and employed a random-effects method for our panel dataset. Standard errors were clustered by firm in our regression estimation. Our results suggest that direct method cash flow components enhance the predictive ability of aggregate operating cash flow for up to a four-year forecast horizon. These results are robust to a battery of sensitivity tests. We also find that cash received from customers and cash paid to suppliers and employees complement each other in enhancing the overall predictive ability of cash flow components. Moreover, the predictive ability of both aggregate operating cash flow and direct method cash flow components are noticeably higher when the operating cash cycle is short, the firm is large, the firm is profitable, or the firm generates positive net operating cash flow.

Our findings directly contribute to the policy debate as to whether the direct method should be mandated by accounting standard setters. In particular, the current joint project of the IASB and the FASB, the 'Financial Statement Presentation', has emphasized the reporting of disaggregated cash flows under the direct method (FASB, 2010; IFRS Foundation, 2010b). In addition, there have been calls from user groups for the mandatory reporting of the direct method. Our results clearly indicate that, at least for cash flow forecasting, the direct method cash flow statements provide information that is more useful to investors, analysts, and others than the aggregate operating cash flow reported by way of the indirect method.

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Table 1
Comparison between the sample and the ASX market (the population) by industry sectors and firm size.

Panel A: Comparison by industry sectors

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%

Panel B: Comparison by firm size (total assets): 1992 to 2004

	Total assets					
	Mean			**Median**		**Mann-Whitney**
Year	**Market**	**Sample**	***t*-statistic**	**Market**	**Sample**	***z* statistic**
1992	529.58	503.19	0.112	7.44	9.09	0.751
1993	519.24	531.88	0.054	8.65	11.12	0.887
1994	499.41	552.70	0.245	11.56	15.34	1.186
1995	561.08	654.72	0.392	14.48	16.97	0.782
1996	529.69	664.05	0.593	18.25	19.28	0.337
1997	539.95	719.97	0.831	20.88	21.32	0.400
1998	575.16	764.42	0.832	22.49	20.77	0.019
1999	567.39	770.03	0.854	20.75	21.95	0.488
2000	646.36	874.75	0.729	24.47	26.06	0.544
2001	752.39	1015.10	0.714	22.05	24.77	0.895
2002	729.28	1045.08	0.908	20.88	25.29	1.871^{*}
2003	680.96	1018.02	1.031	18.31	23.25	1.975^{**}
2004	658.67	1063.59	1.314	20.01	28.71	$2.594^{\dagger}$

Notes:
(1) Comparisons in Panels A and B are based on the initial sample containing 349 firms.
(2) 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).
(3) ASX market composition is based on the number of the listed firms on the ASX capital market in 1992 by industry sectors, excluding firms in the Financials sector. The data are extracted from the *Aspect Financial Analysis* database.
(4) The *t*-statistic refers to the result of the *t*-test for testing the significance of the difference between the sample and the population means.
(5) The *Z*-statistic refers to the result of the non-parametric Mann-Whitney *U*-test for testing the difference between the sample and the population medians.
(6) †,**,* indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 2
Summary statistics and correlation matrix.

Panel A: Sample descriptive statistics by market capitalization and total assets

Variable	Mean	1st Quartile	Median	Third Quartile	Std. Dev.
Market capitalization (Australian $ million)	1778.47	6.37	19.25	118.15	2156.26
Total assets (Australian $ million)	782.88	5.50	19.68	117.39	4642.8

Panel B: Sample descriptive statistics for model variables (4520 firm-years, 1992–2004)

Variable	Mean	1st Quartile	Median	Third Quartile	Std. Dev.
CF	0.18	-0.01	0.00	0.21	0.47
CSHRD	2.57	0.00	0.15	2.25	6.53
CSHPD	2.34	0.01	0.14	1.88	6.23
INTPD	0.02	0.02	0.00	0.00	0.12
TXPD	0.04	0.00	0.00	0.03	0.12
OTHCSH	0.01	0.00	0.00	0.00	0.35

Panel C: Pearson correlation matrix

	CF	*CSHRD*	*CSHPD*	*INTPD*	*TXPD*	*OTHCSH*
CF	1.00					
CSHRD	0.44†	1.00				
CSHPD	0.40†	0.99†	1.00			
INTPD	0.11†	0.19†	0.18†	100		
TXPD	0.58†	0.50†	0.48†	-0.07†	1.00	
OTHCSH	0.37†	-0.04**	-0.02	0.03**	-0.18†	1.00

Notes:

(1) Variable definition: *CF* is net cash flow from operating activities reported in 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.

(2) All variables are scaled by the number of ordinary shares outstanding at year-end.

(3) †,** indicate statistical significance at the 0.01 and 0.05 levels, respectively.

(4) The sample for total assets comprises 4,537 firm-year observations during the period 1992–2004. The sample for market capitalization consists of 3,141 firm-year observations during the period 1996–2004 because we do not have market value data for our sample firms for 1992–1995.

(5) The correlation matrix in panel C is based on non-signed variables.

Table 3
Predictive ability of aggregate operating cash flow and direct method cash flow components for future cash flows.

Panel A: Predicting current *CF* with one-year lagged *CF* or direct method cash flow components

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

$$\text{Model (2)}: CF_{it} = \beta_0 + \beta_1 CSHRD_{it-1} + \beta_2 CSHPD_{it-1} + \beta_3 INTPD_{it-1} + \beta_4 TXPD_{it-1} + \beta_5 OTHCSH_{it-1} + \varepsilon_{it}$$

	One-Year Lag			
	Model (1)		Model (2)	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	0.04	4.96†	0.03	3.45†
CF	0.76	15.63†		
CSHRD			0.64	9.26†
CSHPD			-0.63	-9.08†
INTPD			-0.45	-2.89†
TXPD			0.01	0.02
OTHCSH			0.71	11.93†
Adjusted R^2	53%		55%	
Tests of coefficient restrictions:				
Null hypothesis			χ^2 statistic	*p*-value
$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$			18.02	0.00
N	3,127		3,127	

Panel B: Predicting current *CF* with two-year lagged *CF* or direct method cash flow components

$$\text{Model (1a)}: CF_{it} = \alpha_0 + \alpha_1 CF_{it-2} + \varepsilon_{it}$$

$$\text{Model (2a)}: CF_{it} = \beta_0 + \beta_1 CSHRD_{it-2} + \beta_2 CSHPD_{it-2} + \beta_3 INTPD_{it-2} + \beta_4 TXPD_{it-2} + \beta_5 OTHCSH_{it-2} + \varepsilon_{it}$$

	Two-Year Lag			
	Model (1)		Model (2)	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	0.06	4.11†	0.04	3.05†
CF	0.72	8.72†		
CSHRD			0.55	5.14†
CSHPD			-0.54	-5.13†
INTPD			-0.55	-2.54**
TXPD			0.24	0.53
OTHCSH			0.59	7.02†
Adjusted R^2	44%		48%	
Tests of coefficient restrictions:				
Null hypothesis			χ^2 statistic	*p*-value
$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$			29.47	0.00
N	2,781		2,781	

(Table continued on next page)

Table 3 *(Continued)*

Panel C: Explaining current *CF* with three-year lagged *CF* or direct method cash flow components

$$\text{Model (1b)}: CF_{it} = \alpha_0 + \alpha_1 CF_{it-3} + \varepsilon_{it}$$

$$\text{Model (2b)}: CF_{it} = \beta_0 + \beta_1 CSHRD_{it-3} + \beta_2 CSHPD_{it-3} + \beta_3 INTPD_{it-3} + \beta_4 TXPD_{it-3} + \beta_5 OTHCSH_{it-3} + \varepsilon_{it}$$

	Three-Year Lag			
	Model (1)		Model (2)	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	0.06	4.07†	0.04	3.35†
CF	0.72	7.73†		
CSHRD			0.59	5.31†
CSHPD			-0.58	-5.36†
INTPD			-0.68	-2.88†
TXPD			0.26	0.51
OTHCSH			0.57	6.25†
Adjusted R^2	42%		47%	
Tests of coefficient restrictions:				
Null hypothesis			χ^2 statistic	*p*-value
$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$			37.26	0.00
N	2,433		2,433	

Panel D: Explaining current *CF* with four-year lagged *CF* or direct method cash flow components

$$\text{Model (1c)}: CF_{it} = \alpha_0 + \alpha_1 CF_{it-4} + \varepsilon_{it}$$

$$\text{Model (2c)}: CF_{it} = \beta_0 + \beta_1 CSHRD_{it-4} + \beta_2 CSHPD_{it-4} + \beta_3 INTPD_{it-4} + \beta_4 TXPD_{it-4} + \beta_5 OTHCSH_{it-4} + \varepsilon_{it}$$

	Four-Year Lag			
	Model (1)		Model (2)	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	0.08	4.35†	0.04	3.59†
CF	0.65	6.06†		
CSHRD			0.50	4.42†
CSHPD			-0.49	-4.33†
INTPD			-0.62	-2.57**
TXPD			0.32	0.64
OTHCSH			0.48	4.79†
Adjusted R^2	41%		49%	
Tests of coefficient restrictions:				
Null hypothesis			χ^2 statistic	*p*-value
$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$			27.17	0.00
N	2,085		2,085	

(Table continued on next page)

Table 3 *(Continued)*

Panel E: Summary of results for out-of-sample forecasting tests (1,042 firm-years, 2002–2004)

One-Year Lag	Model (1)	Model (2)
Theil's *U*-statistic	0.36	0.33
Bias proportion	0.01	0.00
Variance proportion	0.11	0.08
Covariance proportion	0.88	0.92

Two-Year Lag	Model (1)	Model (2)
Theil's *U*-statistic	0.38	0.36
Bias proportion	0.00	0.00
Variance proportion	0.09	0.05
Covariance proportion	0.91	0.95

Three-Year Lag	Model (1)	Model (2)
Theil's *U*-statistic	0.39	0.37
Bias proportion	0.00	0.00
Variance proportion	0.09	0.04
Covariance proportion	0.91	0.96

Four-Year Lag	Model (1)	Model (2)
Theil's *U*-statistic	0.42	0.39
Bias proportion	0.00	0.00
Variance proportion	0.16	0.10
Covariance proportion	0.84	0.90

Notes:

(1) *i* and *t* denote firm and year respectively. *CF* 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.

(2) The time random-effects method is used for estimating models (1) and (2).

(3) The *t*-statistic is based on the standard errors clustered by firm.

(4) †,** indicate statistical significance at the 0.01 and 0.05 levels, respectively.

(5) Theil's *U*-statistic is a forecast error statistic lying between 0 and 1, where 1 shows the worst fit. In a good forecast, the bias and variance proportions of Theil's *U*-statistic are smaller than its covariance proportion.

Table 4
Predictive ability of aggregate operating cash flow and direct method cash flow components for future cash flows by industry sectors.

$$\text{Model (1)}: CF_{it} = \alpha_0 + \alpha_1 CF_{it-1} + \varepsilon_{it}$$
$$\text{Model (2)}: CF_{it} = \beta_0 + \beta_1 CSHRD_{it-1} + \beta_2 CSHPD_{it-1} + \beta_3 INTPD_{it-1} + \beta_4 TXPD_{it-1} + \beta_5 OTHCSH_{it-1} + \varepsilon_{it}$$

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

Variable	Energy		Materials		Industrials		Consumer Discretionary	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Intercept	0.01†	0.01†	0.01†	0.00	0.08†	0.03**	0.06†	0.05†
CF	0.84†		0.78†		0.71†		0.79†	
CSHRD		0.64†		0.57†		0.14†		0.33†
CSHPD		-0.65†		-0.54†		-0.11†		-0.32†
INTPD		0.47		-0.52†		0.36		-0.98†
TXPD		0.24		-0.61†		0.76**		0.03
OTHCSH		0.67†		0.50†		-0.23		0.58†
Adjusted R^2	68%	73%	63%	67%	48%	57%	52%	55%
N	284		1223		477		464	

Panel A *(continued)*

Variable	Consumer Staples		Health Care		Information Technology	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Intercept	0.06†	0.04**	0.01*	-0.00	-0.01	-0.01†
CF	0.83†		0.54†		0.19*	
CSHRD		0.56†		0.41†		0.10*
CSHPD		-0.55†		-0.40†		0.09
INTPD		-0.63*		0.15		0.51**
TXPD		-0.44†		0.55		0.08
OTHCSH		0.23†		0.46†		0.21
Adjusted R^2	65%	73%	37%	58%	9%	13%
N	200		159		121	

(Continued on next page)

Table 4 *(continued)*

Panel B: χ^2 tests of coefficient restrictions (null hypothesis: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$)

Industry Sector	χ^2 statistic	*p*-value
Energy	1117.30	0.00
Materials	151.42	0.00
Industrials	184.99	0.00
Consumer Discretionary	10.57	0.03
Consumer Staples	497.94	0.00
Health Care	225.93	0.00
Information Technology	131.08	0.00

Panel C: Summary of results for out-of-sample forecasting tests (2002–2004) - Theil's *U*-statistic

Industry Sector	Model (1)	Model (2)	N
Energy	0.35‡	0.33‡	87
Materials	0.40‡	0.35‡	407
Industrials	0.31‡	0.30‡	159
Consumer Discretionary	0.33‡	0.32‡	153
Consumer Staples	0.31‡	0.29‡	68
Health Care	0.42	0.27‡	52
Information Technology	0.86	0.83	42

Notes:

(1) 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).

(2) *i* and *t* denote firm and year, respectively. *CF* is net cash flow from operating activities in 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.

(3) The time random effects method is used for estimating models (1) and (2).

(4) The *t*-statistic is based on the standard errors clustered by firm.

(5) Theil's *U*-statistic is a forecast error statistic lying between 0 and 1, where 1 shows the worst fit. In a good forecast, the bias and variance proportions of Theil's *U*-statistic are smaller than its covariance proportion.

(6) †,**,* indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. ‡ indicates the covariance proportion is higher than the bias and variance proportions of Theil's *U*-statistic.

Table 5
Predictive ability of aggregate operating cash flow and direct method cash flow components for future cash flows: Year by year estimations (1992–2004).

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

$$\text{Model (2)}: CF_{it} = \beta_0 + \beta_1 CSHRD_{it-1} + \beta_2 CSHPD_{it-1} + \beta_3 INTPD_{it-1} + \beta_4 TXPD_{it-1} + \beta_5 OTHCSH_{it-1} + \varepsilon_{it}$$

	1993		1994		1995		1996	
Variable	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Intercept	0.03†		0.03†	0.02*	0.02**	0.00	0.05†	0.04*
CF	0.75†		0.75†		0.95†		0.72†	
CSHRD		0.77†		0.64†		0.82†		0.66†
CSHPD		-0.76†		-0.63†		-0.81†		-0.65†
INTPD		-0.27†		-0.25		-0.94		-0.75**
TXPD		-0.78†		-0.46*		-0.21		0.49
OTHCSH		0.76†		0.64†		0.84†		0.72†
Adjusted R^2	63%	67%	59%	62%	52%	56%	34%	38%
N	696		696		694		694	

	1997		1998		1999		2000	
Variable	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Intercept	0.05†	0.03†	0.04†	0.04†	0.04†	0.02**	0.03†	0.02**
CF	0.65†		0.77†		0.83†		0.91†	
CSHRD		0.64†		0.59†		0.66†		0.64†
CSHPD		-0.64†		-0.59†		-0.65†		-0.64†
INTPD		-0.74†		-0.48†		-0.42**		-1.04†
TXPD		0.21		-0.18		-0.11		1.09**
OTHCSH		0.51†		0.78†		0.77†		0.70†
Adjusted R^2	74%	75%	65%	67%	68%	71%	67%	74%
N	694		696		696		694	

	2001		2002		2003		2004	
Variable	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Intercept	0.04†	0.03†	0.06†	0.03†	0.07†	0.04†	0.08†	0.04†
CF	0.77†		0.69†		0.66†		0.70†	
CSHRD		0.54†		0.48†		0.50†		0.43†
CSHPD		-0.53†		-0.47†		-0.49†		-0.43†
INTPD		-0.54		-0.02		-0.11		0.05
TXPD		0.33		-0.02		-0.08		0.76
OTHCSH		0.74†		0.70†		0.50†		0.23
Adjusted R^2	59%	61%	53%	57%	50%	53%	51%	59%
N	691		692		694		695	

Notes:

(1) *i* and *t* denote firm and year respectively. *CF* is net cash flow from operating activities in 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.
(2) The OLS method is used for estimating models (1) and (2).
(3) The *t*-statistic is based on standard errors clustered by firm.
(4) †,**,* indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6
Testing for incremental predictive ability of cash received from customers and cash paid to suppliers and employees for future cash flows. A comparison between models (2) and (4), and between models (2) and (5).

$$\text{Model (2)}: CF_{it} = \beta_0 + \beta_1 CSHRD_{it-1} + \beta_2 CSHPD_{it-1} + \beta_3 INTPD_{it-1} + \beta_4 TXPD_{it-1} + \beta_5 OTHCSH_{it-1} + \varepsilon_{it}$$
$$\text{Model (4)}: CF_{it} = \gamma_0 + \gamma_1 CSHRD_{it-1} + \gamma_2 INTPD_{it-1} + \gamma_3 TXPD_{it-1} + \gamma_4 OTHCSH_{it-1} + \varepsilon_{it}$$
$$\text{Model (5)}: CF_{it} = \delta_0 + \delta_1 CSHPD_{it-1} + \delta_2 INTPD_{it-1} + \delta_3 TXPD_{it-1} + \delta_4 OTHCSH_{it-1} + \varepsilon_{it}$$

Panel A: Explaining current *CF* with one-year lagged direct method cash flow components

	Model (2)		Model (4)		Model (5)	
Variable	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Intercept	0.03	3.45†	0.06	4.24†	0.06	4.32†
CSHRD	0.64	9.26†	0.02	2.23**		
CSHPD	-0.63	-9.08†			0.01	1.99**
INTPD	-0.45	-2.89†	0.29	1.05	0.33	1.18
TXPD	0.01	0.02	1.44	2.61†	1.54	2.76†
OTHCSH	0.71	11.93†	0.34	2.12**	0.32	2.01**
Adjusted R^2	55%		38%		37%	
Tests of coefficient restrictions:						
Null hypothesis	χ^2 statistic	*p*-value				
$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$	18.02	0.00				
$\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4$	18.23	0.00				
$\delta_1 = \delta_2 = \delta_3 = \delta_4$	20.57	0.00				
N	3,127		3,127		3,127	

Panel B: Summary of results for out-of-sample forecasting tests (1,042 firm-years, 2002–2004)

One-Year Lag	Model (2)	Model (4)	Model (5)
Theil's *U*-statistic	0.33	0.39	0.40
Bias proportion	0.00	0.02	0.00
Variance proportion	0.08	0.17	0.18
Covariance proportion	0.92	0.83	0.82

Notes:
(1) *i* and *t* denote firm and year respectively. *CF* is net cash flow from operating activities in 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.
(2) The random-effects method is used for estimating models (2), (4) and (5).
(3) The *t*-statistics are based on the standard errors clustered by firm.
(4) †,** indicate statistical significance at the 0.01 and 0.05 levels, respectively.
(5) Theil's *U*-statistic is a forecast error statistic lying between 0 and 1, where 1 shows the worst fit. In a good forecast, the bias and variance proportions of Theil's *U*-statistic are smaller than its covariance proportion.