# Cash Flow Disaggregation and Prediction of Cash Flow


## Abstract

**Purpose –** This paper aims to investigate the incremental information content of estimates of cash flow components in predicting future cash flows.

**Design/methodology/approach –** The authors examine whether models incorporating components of operating cash flow (OCF) from income statements and balance sheets using the direct method are associated with smaller prediction errors than models incorporating core and non-core cash flow.

**Findings –** Using US and UK data and multiple regression analysis, we find that around 60% of a current year's cash flow will persist into the next period's cash flows, and that income statement and balance sheet variables persist similarly. The explanatory power and predictive ability of disaggregated cash flow models are superior to that of an aggregated model, and further disaggregating previously applied core and non-core cash flows provides incremental information about income statement and balance sheet items that enhances prediction of future cash flows. Disaggregated models and their components produce lower out-of-sample prediction errors than an aggregated model.

**Research limitations/implications –** This study improves our appreciation of the behaviour of cash flow components and confirms the need for detailed cash flow information in accordance with the articulation of financial statements.

**Practical implications –** Our findings are relevant to investors and analysts in predicting future cash flow and to regulators with respect to disclosure requirements and recommendations.

**Originality/value –** This paper contributes to the existing literature by further disaggregating cash flow items into their underlying items from income statements and balance sheets.

**Keywords** Core and non-core cash flows, Articulation of financial statements, Income statement, Balance sheet, Cash flow statement, Prediction of future cash flows, Accruals

**Paper type** Research paper

## 1. Introduction

The official accounting standards – both SFAS 95 and IAS 7 – allow managers to choose either the direct method or the indirect method in preparing cash flow statements. However, both the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) have suggested that the direct method must be mandatory for all firms. The implications of these methods for prediction of operating cash flow (OCF) have been studied in the accounting literature. Most studies (e.g., Dechow, 1994; Cheng *et al.*, 1996; Barth *et al.*, 2001; Orpurt and Yoonseok, 2009; Arthur *et al.*, 2010; Hales and Orpurt, 2013; Farshadfar and Monem, 2013; Christodoulou and McLeay, 2014) have shown that cash flow is a fundamental tool for evaluating firm value and a potent mechanism for analysis of a firm's future value. Studies conducted by Cheng and Hollie (2008), Arthur *et al.* (2010), Hales and Orpurt (2013), Farshadfar and Monem (2013), and Christodoulou and McLeay (2014) have also shown that information in the form of aggregate OCF, consisting of core and non-core components, differentially persists in terms of the future cash flow. Core and non-core cash flow can be identified by their functional properties, i.e., consistent with core and non-core earnings in an income statement, or by their persistence level: persistent items are classified as core items and those that do not persist are classified as non-core items.

The aforementioned studies enhanced our understanding of the significance of the cash flow statement, further to which we sought to examine the role of cash flow components (particularly from balance sheets and income statements) in predicting future cash flows beyond the distinction between core and non-core cash flows. We expected incremental information from these components, which would lead to substantial improvements in predicting future cash flow. In addition, we expected income statement items to persist more strongly than balance sheet items, as they contain both accrual and cash information.

In this study, we used estimates of cash flow components to investigate the prediction of future cash flow. Consistent with the work of Cheng and Hollie (2008), we compared the core cash flow components (cash flows related to sales, cost of goods sold, and other operating expenses) with non-core cash flow components (cash flows related to interest, taxes, and other expenses) for both US and UK companies to determine whether they give differential signals with respect to future OCF.

We investigated further by disaggregating the components of core and non-core cash flow into their underlying items from balance sheets and income statements, hypothesising that by using the direct method, information in the form of core and non-core cash flows includes both income statement information and balance sheet information, which have differential signals for future cash flow.

Using pair-wise comparisons and out-of-sample prediction, our findings show that all three components of core cash flow persist more strongly and produce lower out-of-sample prediction errors than the three components of non-core cash flow. In addition, the model that disaggregates OCF into components of core and non-core cash flow has higher explanatory power, predictive ability, and lower prediction error than the model simply incorporating aggregate cash flow. Our findings are consistent after disaggregating the components of core and non-core cash flow into their underlying items from income statements and balance sheets. Our study contributes in three ways. First, it extends the existing literature on disaggregating cash flow by further disaggregating cash flow items into their underlying items from fundamental financial statements (income statements and balance sheets). Second, our work supports the joint FASB/IASB Financial Statement Presentation project[1], specifically that the quality of financial statements should be improved, as an extreme degree of aggregation and netting of items in statements causes investors to resort to estimates and 'best guesses' of information essential for financial decision-making. Third, our study represents a significant advance over previous work in that we employed both UK and US data, thus maximising the validity and generalisability of our results.

The remainder of this paper is organised as follows. Section 2 provides a review of the relevant literature. Section 3 describes our hypotheses development and research design, and addresses the methodological issues. Section 4 presents the sample selection criteria and discusses our empirical findings. Finally, in Section 5, we summarise and conclude the paper.

## 2. Literature Review

To date most studies have confirmed the superiority of disaggregated models over aggregated ones (Krishnan and Largay, 2000; Barth *et al.*, 2001; Arthur *et al.*, 2010; Malacrida *et al.*, 2010; Lev *et al.*, 2010; Dargenidou *et al.*, 2011; Christodoulou and McLeay, 2014). For example, a seminal empirical study by Krishnan and Largay (2000) examined the ability of cash flow components to predict future cash flow. Their findings showed that, in predicting OCF one year ahead, mean average percentage errors (MAPE) and average ranks are smaller for disaggregated models than models that use only earnings and accruals information. Barth *et al.* (2001) showed that disaggregating accruals into major components – change in accounts receivable, change in accounts payable, change in inventory, depreciation, amortisation, and other accruals – significantly enhances the predictive ability of future cash flow. They asserted that each accrual component reflects different information related to past transactions, thus affecting prediction, and that aggregate earnings masks this information.

Cheng and Hollie (2008) showed that cash flow components from various operating activities persist differentially, but, more specifically, core cash flow items (cash flows related to sales, the cost of goods sold, and other operating expenses) persist more strongly than non-core cash flow items (cash flows related to interest, tax, and other expenses). They also found that the three components of core cash flow have similar persistence, and greater persistence than the three components of non-core cash flow.

Arthur *et al.* (2010) explored the way in which aggregated and disaggregated models are compared, finding that a cash flow components model is superior to an aggregated cash flow model in terms of explanatory power and predictive ability for future earnings, and that disclosure of core and non-core cash flow components is useful in both respects. Their findings are consistent with the work of Cheng and Hollie (2008) (despite their investigation being in the context of prediction of future earnings, rather than prediction of future cash flows).

A further study by Farshadfar and Monem (2013) provides evidence that disaggregating operating cash flow into its components improves the predictive ability of aggregate operating cash flow in forecasting future cash flows for up to a four-year forecast horizon. They also found that cash received from customers and cash paid to suppliers and employees complement each other in improving the overall predictive ability of cash flow components. Despite their investigation being based on pre-IFRS data from Australia, their findings are consistent with the work of Cheng and Hollie (2008) . Moreover, they found the predictive ability of both aggregate operating cash flow and direct method cash flow components to be 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 study employed both UK and US data, whereas the studies by Farshadfar and Monem (2013) and Arthur *et al.* (2010) are based on data from Australia. Also, unlike our study, which uses estimates of cash flow components in predicting future cash flows, the earlier studies of Farshadfar and Monem (2013) and Arthur *et al.* (2010) use actual cash flow components under the direct method, as per Australian Accounting Standards Board (AASB) 1026: Statement of Cash Flows (AASB, 1991; revised AASB (1997)).

Finally, a study by Hales and Orpurt (2013) reviews all academic literature related to cash flow reporting during the past two decades, aiming to ascertain what incremental benefits might be gained by disaggregating cash flow items.

## 3. Hypotheses development and research design

Accounting standards allow managers to choose the direct method or the indirect method in preparing cash flow statements; due to the extreme degree of aggregation in financial statements, investors have to resort to estimates and ‘best guesses’ of information essential for financial decision-making. Discretionary disclosure theory suggests that proprietary costs are an important reason for firms often withholding material information, such as cash flow information, which is generally viewed as competitively sensitive. Verrecchia and Weber (2006) found that firms in more competitive industries tend to withhold information through redacted disclosures: more intense competition raises the proprietary costs of disclosure. However, evidence from this study, along with the prior literature, suggests that the disclosure of OCF components is beneficial to the prediction of future firm performance. Information about OCF components may help us to understand the major sources and applications of cash from operating activities. As these components are not perfectly correlated, reporting them separately may be more useful than providing them in aggregate.

We applied estimates of cash flow components in predicting future cash flow, initially grouping these components into core and non-core cash flows, given their functional sources, and then disaggregated each component of core and non-core cash flows into their underlying factors from balance sheet and income statements. Figure 1 shows the major elements of the study, presenting the links between the models.

[PLEASE INSERT FIGURE 1 HERE]

Consistent with the prior work (Cheng and Hollie, 2008; Francis and Eason, 2012; Farshadfar and Monem, 2013) suggesting that past OCF enables prediction of future OCF, we present the primary hypothesis of the study:

*H1*: Past operating cash flow operations enables prediction of future operating cash flow.

In the first model (Model 1), operating cash flow is predicted based solely on aggregated information from the last period.

Model 1 focused on cash flow information with the coefficients of the components of OCF constrained to be equal. Both sides of the model are current and one-year-ahead OCF:

$$OCF_{t+1} = \propto + \beta_1 \sum OCF_t + \mu_t \qquad (1)$$

The American Institute of Certified Public Accountants (AICPA) recommends that firms should distinguish between the financial effects of a company's core (major or central operations) and non-core (peripheral or incidental activities) cash flows. Furthermore, Farshadfar and Monem (2013) note that disaggregating OCF into major components significantly improves the predictive ability of future OCF, because aggregate OCF masks their information content. Consistent with the AICPA's recommendation and Farshadfar and Monem (2013), the second model (Model 2) disaggregates OCF information in Model 1 into core and non-core cash flow components and gradually relaxes the constraint. Using Model 2, we examined if there are different levels of information contained in core and non-core cash flow components in predicting OCF. We conducted pair-wise comparisons of the regression coefficients to test the persistence of cash flow components. Consistent with the work of Cheng and Hollie (2008), our second hypothesis was:

*H2:* In predicting OCF, the information content of the components of the core and non-core OCF is more valuable than its aggregate.

Therefore, Model 2 is presented as follows:

$$OCF_{t+1} = \propto + \beta_1 C\_SALES_t + \beta_2 C\_COGS_t + \beta_3 C\_OE_t + \beta_4 C\_INT_t + \beta_5 C\_TAX_t + \beta_6 C\_OTHER_t + \mu_t \qquad (2)$$

where C_SALES = cash flows related to sales; C_COGS = cash flows related to cost of goods sold; C_OE = cash flows related to other operating expenses; C_INT = cash flows related to interest; C_TAX = cash flows related to tax; and C_OTHER = cash flows related to other revenue/expenses.

The third model (Model 3) disaggregated the OCF information presented in Model 2 into the components of balance sheet and income statement.

Our third hypothesis was:

*H3*: In predicting future cash flows, the information content of the income statement and balance sheet items is incrementally more informative than the core and non-core cash flow components.

Our third mathematical model is shown below.

$$OCF_{t+1} = \propto + \beta_1 SAL_t + \beta_2 \Delta ARE_t + \beta_3 CGS_t + \beta_4 \beta_4 SAE_t + \beta_5 \Delta APA_t + \beta_6 \Delta INV_t + \beta_7 \Delta ACP_t + \beta_8 OOE_t + \beta_9 DDA_t + \beta_{10} \Delta OCL_t + \beta_{11} \Delta OCA_t + \beta_{12} IED_t + \beta_{13} IIN_t + \beta_{14} \Delta STD_t + \beta_{15} ITX_t + \beta_{16} \Delta ITP_t + \beta_{17} \Delta DTX_t + \beta_{18} C\_OTHER_t + \mu_t \quad (3)$$

where SAL = sales; ΔARE = changes in accounts receivable; CGS = cost of goods sold; SAE = selling and administrative expenses; ΔAPA = changes in accounts payable; ΔINV = changes in inventories; ΔACP = changes in accrued payroll; OOE = other operating expenses; DDA = depreciation, depletion, and amortisation; ΔOCL = changes in other current liabilities; ΔOCA = changes in other current assets; IED = interest expense on debt; IIN = interest income; ΔSTD = changes in short term debt; ITX = income tax; ΔITP = changes in income tax payable; ΔDTX = changes in deferred tax; and C_OTHER = cash flows related to other revenue/expenses.

Contrasting Models 2 and 3 provided evidence as to whether income statement items and balance sheet items are incrementally informative beyond core and non-core cash flow components in predicting future cash flows.

## 4. Data and Results

### 4.1 *Descriptive Statistics*

We obtained financial data from Wordscope for the years 1995–2009 for both UK- and US-listed firms. We use a working sample of 2,126 firms and 22,512 firm-year observations for the US and 413 firms and 4,958 firm-year observations for the UK.

Table I, Panel A presents descriptive statistics for the regression variables in Model 2. All the variables were scaled by total assets. The deflator is chosen to mitigate heteroscedasticity. As in Cheng and Hollie (2008) and Arthur *et al.* (2010), we deflate by total assets, as this measure is not affected by differences in capital structure.

Consistent with the work of Arya *et al.* (2000), Barth *et al.* (2001), Arya *et al.* (2004), Cheng and Hollie (2008), and Christodoulou and McLeay (2014), positive (negative) signs are allocated to all cash inflow (outflow). Contrasting the medians with the means for both US and UK firms showed that OCF is skewed to the left (for US firms, the median is 0.060 and the mean is 0.050; for UK firms, the median is 0.046 and the mean is 0.038). Furthermore, C_SALES and C_COGS for both US and UK firms have substantially larger means (1.017 and -0.700 for US firms; 1.143 and -0.524 for UK firms) relative to all other cash flow components, suggesting that these two components may explain most of the total variation in OCF. Using a t-test, Table I, Panels B and C compare the means for both US and UK firms respectively. The t-test results are significant at less than 1 percent for all variables, indicating that means are not statistically similar across both US and UK firms.

[INSERT TABLE I ABOUT HERE]

Table II, Panel A reports means for the regression variables in Model 3 for both US and UK firms, which combines items from income statements (sales; cost of goods sold; selling and administrative expenses; other operating expenses; depreciation, depletion, and amortisation; interest expense on debt; interest income; and income taxes) with items from balance sheets (changes in accounts receivable, accounts payable, inventory, accrued payrolls, other current liabilities, other current assets, short-term debt, income tax payable, and deferred tax).

[INSERT TABLE II ABOUT HERE]

4.2. *Inferential Statistics*

Pearson and Spearman correlation coefficients were calculated for all regression variables, but, for brevity, the tables are not presented [2]. Correlation coefficients between C_SALES and C_COGS for both US and UK firms were particularly high (–0.924 and –0.893 for Pearson and Spearman respectively for US firms; -0.923 and -0.913 for UK firms), which could signal potential multicollinearity problems.

To test for multicollinearity, we ran a diagnostic test: variance inflation factor (VIF). Chatterjee *et al*. (2000) and Baum (2003) recommend a maximum VIF of 10, otherwise the estimates are too sensitive (i.e. unstable) to even small changes in the data. Table II, Panels B and C report the multicollinearity test results for Models 2 and 3 respectively.

In Table II, Panel B we found the highest degree of VIFs to be 3.64 and 3.58 for C_SALES and C_COGS respectively, which are well below the maximum recommended VIF level in the literature. Binkley (1982) notes that some degree of multicollinearity is unavoidable, especially in accounting models that rely on such highly structured information.

### 4.3 *Cash flow prediction*

Regression results for both US and UK firms are presented in Table III. Panels A and B report the results for Model 1, in which aggregated cash flows predict the next year's cash flow. For both US and UK firms, we found that aggregated cash flows are significantly associated with future cash flows. OCF explains around one-third of the variation in next year's cash flows. Around 60% of the current year's cash flows will persist into the next period's cash flows.

Our study represents a significant advance over the work of Cheng and Hollie (2008), in that we employed both UK and US data, thus maximising the validity and generalisability of our results. The outcomes of Model 2 (relating to Hypothesis 2) are presented in Panels C and D of Table III. The adjusted $R^2$ for US firms increased 9% and 6% for UK firms from the respective values generated with Model 1. Consistent with previous studies, we find all cash flow components are significant and positive predictors of future cash flows (except C_TAX, which is a negative and insignificant predictor). C_TAX has low persistence because it is associated with all aspects of the business, including operating and non-operating activities. Moreover, unlike other cash flow components, which are affected by managers' operating, financing, and investment activities, taxes are determined mostly by tax policies and a firm's tax strategies.

[INSERT TABLE III ABOUT HERE]

The coefficients for core cash flows (C_SALES, C_COGS, and C_OE) suggest that all core components have similar persistence in both markets. Note that the coefficients for C_OTHER are larger than those for C_INT. Although C_INT is associated with financing activities, the FASB decided, in SFAS 95, that it should be included in the operating part of the cash flow section. Our findings of high persistence for interest provide additional confirmation for the FASB's decision.

To test Hypothesis 2, we also ran pair-wise tests of the differences in the coefficients of Model 2 for both US and UK firms. Panels E and F of Table III present the results. A negative value for the mean pair-wise comparison indicates that the cash flow item in the row is less persistent than the cash flow item in the column: for instance, in comparing C_COGS and C_TAX for US firms, a mean difference of –.649, a t-statistic of –19.39, and a p-value of < .0001 suggest that cash flows from taxes are less persistent than cash flows related to the cost of goods sold in prediction of future cash flows.

Table III shows that all the coefficients were negative when comparing core cash flow components with non-core cash flow components. Therefore, it can be concluded that core cash flow components persist similarly, and are more persistent than non-core cash flows.

Another significant advance on Cheng and Hollie (2008) is that we further decomposed the components of core and non-core cash flows, as mentioned in their work, into their underlying items from balance sheets and income statements to predict future cash flows. Table IV presents the regression results for Model 3, concerning Hypothesis 3 and relating to these underlying items. Panels A and B report the results for US and UK firms respectively. The adjusted $R^2$ increased 5% for US firms and 7% for UK firms over the respective values generated by Model 2. All balance sheet and income statement items except ΔITP, ΔDTX, and ITX were significant positive predictors of future cash flows for both US and UK firms.

[INSERT TABLE IV ABOUT HERE]

The coefficients for the income statement items SAL, CGS, SAE, OOE, and DDA suggest that components of core cash flow from income statements have similar persistence for both US and UK firms. Consistent with Model 2, the underlying items for C_INT from income statements, IED and IIN, are significant and positive predictors. This finding of high persistence for IED and IIN provides additional confirmation for the FASB's decision to include interest payments in the OCF section of the cash flow statement.

The same behaviour was found across balance sheet variables as the coefficients for ∆ARE, ∆APA, ∆INV, ∆ACP, ∆OCL, and ∆OCA have similar persistence. Consistent with Model 2, the underlying items associated with C_TAX (ITX, ∆ITP, and ∆DTX) have low persistence.

Our adjusted $R^2$ increased substantially between Models 1 and 3. Table V presents a pair-wise comparison test between each model's adjusted R-squares. The between-model increases are all significantly different from zero. We conclude that disaggregating cash flows into core and non-core components and then into their underlying items from balance sheets and income statements enhances in-sample predictability.

[INSERT TABLE V ABOUT HERE]

We defined in-sample prediction error as the absolute value of the residuals from the prediction models. However, the improvement in in-sample prediction is not associated with out-of-sample prediction errors. In-sample predictability presents the underlying structure of the relationship between the variables, whereas out-of-sample predictability reports the stability of the coefficients across time.

In-sample prediction errors are presented in Table VI. In Panel A the distribution statistics of the in-sample prediction errors for Models 1, 2, and 3 are reported as |l(1)|, |l(2)|, and |l(3)|. We also report the differences between Models 1 and 2 as |l(2)| – |l(1)|, representing the improvement resulting from disaggregating cash flow into core and non-core cash flow components, and also between Models 2 and 3 as |l(3)| – |l(2)|, representing the improvement resulting from disaggregating the core and non-core cash flows into their underlying items from balance sheets and income statements.

The difference between the prediction errors for Models 2 and 1 has a mean of –0.004, representing an improvement of approximately 5%. The negative difference specifies the improvement in the in-sample prediction errors when introducing disaggregated variables. Moreover, the difference between the prediction errors for Models 3 and 2 has a mean of –0.003 representing an improvement of 3%. The distributions are skewed to the left, as the medians are larger than the means for comparisons between Models 1 and 2 and Models 2 and 3. This indicates that the mean improvement for the more complex model is driven by over-performance.

[INSERT TABLE VI ABOUT HERE]

Correlation analysis for Models 1, 2, and 3 and the differences between them are presented in Panel B of Table VI. The negative correlation between $|l(2)| - |l(1)|$ and $|l(1)|$ and $|l(3)| - |l(2)|$ and $|l(2)|$ specifies that the enhancement is greater for high forecast error prior to the disaggregation procedure.

Panels A and B in Table VII present the out-of-Sample prediction results for both US and UK firms respectively. Median paired forecast error differences, symmetric mean paired error differences, and Theil's U-statistics indicate that Model 2’s forecast measures are significantly more accurate than Model 1’s measures and that Model 3’s forecast measures are also significantly more accurate than Model 2’s measures. For example, for US firms, Model 2’s median forecast measure is, on average, 8.9% more accurate than Model 1’s measure, and Model 3’s median forecast measure is, on average, 11.2% more accurate than Model 2’s measure. Furthermore, Model 2’s symmetric mean forecast measure is, on average, 3.6% more accurate than Model 1’s measure, and Model 3’s symmetric mean forecast measure is, on average, 7.5% more accurate than Model 2’s measure. Note that the corresponding Theil's U-statistic for Model 2 over Model 1 is 0.912 and for Model 3 over Model 2 is 0.889.

[INSERT TABLE VII ABOUT HERE]

Consistent with the literature, our results suggest that reporting the components of OCF separately is more useful than providing them in aggregate, and the predictive ability of the disaggregated models are superior to an aggregated cash flow model.

## 5. Summary and conclusions

Consistent with the work of Cheng and Hollie (2008), we defined core and non-core cash flows based on their association with the functional categorisation of the income statement. Therefore, all cash flows associated with operations – such as cash flows related to sales, the cost of goods sold, and operating expenses – are categorised as core cash flows, and all cash flows associated with interest, taxes, and other expenses are categorised as non-core cash flows.

Based on mean analysis of coefficients, our findings show that all core cash flow components persist more than non-core cash flow components. This is consistent with the works of Arthur *et al.* (2010), Cheng and Hollie (2008), and Krishnan and Largay (2000). In addition, the core cash flow components have similar persistence. Regarding the non-core cash flow components, cash flow related to taxes is associated with the lowest persistence, and cash flow related to other expenses has higher persistence than cash flows related to interest. We also tested whether decomposing cash flow into core and non-core cash flow components improved in-sample cash flow prediction, finding that this was the case. Therefore, the inclusion of core and non-core cash flow components significantly improves cash flow prediction, and all six components of core and non-core cash flows provide substantial improvement in cash flow prediction beyond that of aggregated cash flows.

Inclusion of income statement and balance sheet items significantly improves cash flow prediction and all the above components provide substantial enhancement in cash flow prediction beyond that of the six core and non-core cash flow components. Moreover, our results show that all income statement items persist more than balance sheet items, and suggest that this differential persistence is related to the greater volume of information contained in income statement variables, as they include both accruals and cash information. Furthermore, income statement and balance sheet items have similar persistence among their groups in prediction of future cash flow.

Our study offers three contributions. First, it extends the existing literature on disaggregating cash flow by further disaggregating cash flow items into their underlying items from income statements and balance sheets. Second, our evidence supports the position of the FASB/IASB Financial Statement Presentation project that the quality of financial statements should be improved, as the extreme degree of aggregation and netting of items in the statements cause investors to resort to estimates and 'best guesses' of information essential for financial decision-making. Third, our study represents a significant advance on previous work in that we employed both UK and US data, thus maximising the validity and generalisability of our results.

Our results support the position on cash flow of both the IASB's and the FASB, suggesting that the direct method must be mandatory for all firms. More importantly, we add to mounting evidence that OCF components convey important information to investors beyond OCF as a summary measure. Practical application of our findings would also assist market analysts in formulating superior cash flow forecasts. Our findings are relevant to academic researchers using cash flow prediction models as a measurement; they are also relevant to financial statement users interested in better predicting a firm's future cash flows and, thereby, its firm value.

In addition, our findings will also have implications for firms in accounting jurisdictions that permit voluntary direct method disclosure. Discretionary disclosure theory notes that as cash flows information is generally viewed as competitively sensitive, firms often withhold this information. However, our findings show that the disclosure of OCF components enhances prediction of future firm performance. This is, essentially, an incentive for firms to disclose such information in order to reduce information asymmetry, pre-empt costly private information acquisition, and lower their cost of raising capital (Diamond, 1985; Diamond and Verrecchia, 1991; Verrecchia, 1983, 1990).

## Notes

1. FASB/IASB Joint Board Meeting, 13 May 2005; and IASB Meeting Summary (Phase A: IAS 1 Presentation of Financial Statements), 14 December 2006, London.
2. For each country, we have a matrix of 25 variables; therefore, for brevity, we only report the outcomes.

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**TABLES:**

**Table I.**

**Panel A -** Descriptive statistics on cash flows and components of cash flows for US & UK firms (Model 2)

| **STATS (US)** | **OCF** | **C_SALES** | **C_COGS** | **C_OE** | **C_INT** | **C_TAX** | **C_OTHER** |
|---|---|---|---|---|---|---|---|
| Mean | 0.050 | 1.017 | -0.700 | -0.236 | -0.013 | -0.067 | 0.050 |
| Std Dev | 0.102 | 0.630 | 0.542 | 0.220 | 0.017 | 0.029 | 0.063 |
| Median | 0.060 | 0.915 | -0.584 | -0.195 | -0.011 | -0.009 | 0.012 |
| N | 22512 | | | | | | |
| **STATS (UK)** | **OCF** | **C_SALES** | **C_COGS** | **C_OE** | **C_INT** | **C_TAX** | **C_OTHER** |
| Mean | 0.038 | 1.143 | -0.524 | -0.176 | -0.109 | -0.305 | 0.010 |
| Std Dev | 0.077 | 0.473 | 0.340 | 0.382 | 0.014 | 0.049 | 0.048 |
| Median | 0.046 | 1.599 | -0.437 | -0.344 | -0.007 | -0.006 | 0.010 |
| N | 4958 | | | | | | |

**Panel B -** Pair-wise t-test (p-value) of means for US firms

| Variable | C_SALES | C_COGS | C_OE | C_INT | C_TAX | C_OTHER |
|---|---|---|---|---|---|---|
| C_SALES | | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* |
| C_COGS | *<.0001* | | *<.0001* | *<.0001* | *<.0001* | *<.0001* |
| C_OE | *<.0001* | *<.0001* | | *<.0001* | *<.0001* | *<.0001* |
| C_INT | *<.0001* | *<.0001* | *<.0001* | | *<.0001* | *<.0001* |
| C_TAX | *<.0001* | *<.0001* | *<.0001* | *<.0001* | | *<.0001* |
| C_OTHER | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | |

**Panel C -** Pair-wise t-test (p-value) of means for UK firms

| Variable | C_SALES | C_COGS | C_OE | C_INT | C_TAX | C_OTHER |
|---|---|---|---|---|---|---|
| C_SALES | | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* |
| C_COGS | *<.0001* | | *<.0001* | *<.0001* | *<.0001* | *<.0001* |
| C_OE | *<.0001* | *<.0001* | | *<.0001* | *<.0001* | *<.0001* |
| C_INT | *<.0001* | *<.0001* | *<.0001* | | *<.0001* | *<.0001* |
| C_TAX | *<.0001* | *<.0001* | *<.0001* | *<.0001* | | *<.0001* |
| C_OTHER | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | |

**Table II.**

**Panel A:** Means for regression variables in Model 3

| STATS | SAL | ∆ARE | CGS | SAE | ∆APA | ∆INV | ∆ACP | OOE | DDA |
|---|---|---|---|---|---|---|---|---|---|
| *US(means)* | 1.091 | 0.074 | -0.970 | -0.529 | -0.339 | 0.031 | -0.489 | -0.264 | -0.185 |
| *UK(means)* | 1.205 | 0.065 | -0.747 | -0.189 | -0.298 | 0.27 | -0.378 | -0.141 | -0.038 |
| **STATS** | **∆OCL** | **∆OCA** | **IED** | **IIN** | **∆STD** | **ITX** | **∆ITP** | **∆DTX** | **C_OTHER** |
| *US(means)* | -0.257 | 0.039 | -0.022 | -0.007 | -0.016 | -0.097 | -0.02 | -0.011 | 0.050 |
| *UK(means)* | -0.122 | 0.114 | -0.065 | -0.028 | 0.012 | -0.414 | -0.065 | -0.043 | 0.010 |

**Notes:** This panel presents descriptive statistics for each of the regression variables in Model 3.

**Panel B:** Multicollinearity test results (VIF) – Model 2

| | | | | | |
|---|---|---|---|---|---|
| **C_SALES** | 3.64 | **C_OE** | 2.18 | **C_TAX** | 1.54 |
| **C_COGS** | 3.58 | **C_INT** | 1.96 | **C_OTHER** | 1.23 |

**Panel C:** Multicollinearity test results (VIF) – Model 3

| | | | | | |
|---|---|---|---|---|---|
| **SAL** | 2.76 | **SAE** | 1.65 | **∆ACP** | 1.65 |
| **∆ARE** | 1.74 | **∆APA** | 1.22 | **OOE** | 1.92 |
| **CGS** | 2.87 | **∆INV** | 1.99 | **DDA** | 1.43 |
| **∆OCL** | 1.96 | **IIN** | 1.23 | **∆ITP** | 1.32 |
| **∆OCA** | 1.33 | **∆STD** | 1.87 | **∆DTX** | 1.82 |
| **IED** | 1.75 | **ITX** | 1.22 | **C_OTHER** | 1.27 |

**Table III.**
Regression results and pair-wise test

$$OCF_{t+1} = \propto + \beta_1 \sum CFO_t + \mu_t \quad (1)$$

$$OCF_{t+1} = \propto + \beta_1 C\_SALES_t + \beta_2 C\_COGS_t + \beta_3 C\_OE_t + \beta_4 C\_INT_t + \beta_5 C\_TAX_t + \beta_6 C\_OTHER_t + \mu_t \quad (2)$$

*Panel A: Regression results for Model 1 for US firms*

| | Adj. $R^2$ | Intercept | $OCF_t$ |
|---|---|---|---|
| Yearly Avg. | 34.50% | 0.042 | 0.637 |
| *t-statistic* | | 16.56 | 31.42 |
| *p-value* | | *<.0001* | *<.0001* |
| *n = 22,512* | | | |

*Panel B: Regression results for Model 1 for UK firms*

| | Adj. $R^2$ | Intercept | $OCF_t$ |
|---|---|---|---|
| Yearly Avg. | 29.70% | 0.027 | 0.584 |
| *t-statistic* | | 11.34 | 20.45 |
| *p-value* | | *<.0001* | *<.0001* |
| *n = 4,958* | | | |

*Panel C: Regression results for Model 2 for US firms*

| | Adj. $R^2$ | Intercept | $C\_SALES_t$ | $C\_COGS_t$ | $C\_OE_t$ | $C\_INT_t$ | $C\_TAX_t$ | $C\_OTHER_t$ |
|---|---|---|---|---|---|---|---|---|
| Yearly Avg. | 43.67% | 0.029 | 0.631 | 0.625 | 0.621 | 0.418 | –0.088 | 0.486 |
| *t-statistic* | | 7.35 | 27.46 | 30.42 | 24.93 | 8.74 | –0.51 | 23.72 |
| *p-value* | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | 0.3739 | <.0001 |
| *n = 22,512* | | | | | | | | |

*Panel D: Regression results for Model 2 for UK firms*

| | Adj. $R^2$ | Intercept | $C\_SALES_t$ | $C\_COGS_t$ | $C\_OE_t$ | $C\_INT_t$ | $C\_TAX_t$ | $C\_OTHER_t$ |
|---|---|---|---|---|---|---|---|---|
| Yearly Avg. | 35.65% | 0.018 | 0.567 | 0.555 | 0.543 | 0.356 | –0.065 | 0.387 |
| *t-statistic* | | 5.01 | 21.47 | 27.91 | 25.55 | 7.44 | –0.43 | 14.77 |
| *p-value* | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | 0.3963 | <.0001 |
| *n = 4,958* | | | | | | | | |

*Panel E: Pair-wise test of differences in the coefficients for Model 2 for US firms*

| Variable | C_SALES | C_COGS | C_OE | C_INT | C_TAX | C_OTHER |
|---|---|---|---|---|---|---|
| | | 0.002 | 0.004 | –0.145 | –0.654 | –0.083 |
| | | 0.34 | 0.23 | –3.12 | –18.47 | –4.79 |
| C_SALES | | *0.7629* | *0.6827* | *0.0382* | *<.0001* | *<.0001* |
| | | | 0.005 | –0.149 | –0.649 | –0.083 |
| | | | 0.28 | –3.16 | –19.39 | –4.79 |
| C_COGS | | | *0.6593* | *0.0348* | *<.0001* | *<.0001* |
| | | | | –0.141 | –0.651 | –0.081 |
| | | | | –3.24 | –20.53 | –4.93 |
| C_OE | | | | *0.0314* | *<.0001* | *<.0001* |
| | | | | | –0.392 | 0.064 |
| | | | | | –6.39 | 2.21 |
| C_INT | | | | | *<.0001* | *0.3147* |
| | | | | | | 0.465 |

| | |
|---|---|
| | 16.29 |
| C_TAX | *<.0001* |

*Panel F: Pair-wise test of differences in the coefficients for Model 2 for UK firms*

| Variable | C_SALES | C_COGS | C_OE | C_INT | C_TAX | C_OTHER |
|---|---|---|---|---|---|---|
| | | 0.003 | 0.005 | –0.217 | –0.513 | –0.069 |
| | | 0.29 | 0.21 | –3.94 | –16.21 | –5.21 |
| C_SALES | | *0.6328* | *0.7379* | *0.0316* | *<.0001* | |
| | | | 0.004 | –0.128 | –0.569 | –0.073 |
| | | | 0.31 | –2.69 | –23.54 | –4.21 |
| C_COGS | | | *0.5482* | *0.0311* | *<.0001* | *<.0001* |
| | | | | –0.128 | –0.727 | –0.088 |
| | | | | –4.19 | –21.28 | –4.78 |
| C_OE | | | | *0.0366* | *<.0001* | *<.0001* |
| | | | | | –0.286 | 0.074 |
| | | | | | –7.13 | 3.17 |
| C_INT | | | | | *<.0001* | *0.3275* |
| | | | | | | 0.548 |
| | | | | | | 17.62 |
| C_TAX | | | | | | *<.0001* |

**Notes:** This table presents regression results for Models 1 and 2 for both US and UK. It also presents the pair-wise test of differences in the coefficients for Model 2 for US.

**Table IV.**

Regression results for Model 3

$$OCF_{t+1} = \propto + \beta_1 SAL_t + \beta_2 \Delta ARE_t + \beta_3 CGS_t + \beta_4 \beta_4 SAE_t + \beta_5 \Delta APA_t + \beta_6 \Delta INV_t + \beta_7 \Delta ACP_t + \beta_8 OOE_t + \beta_9 DDA_t + \beta_{10} \Delta OCL_t + \beta_{11} \Delta OCA_t + \beta_{12} IED_t + \beta_{13} IIN_t + \beta_{14} \Delta STD_t + \beta_{15} ITX_t + \beta_{16} \Delta ITP_t + \beta_{17} \Delta DTX_t + \beta_{18} C - OTHER_t + \mu_t \quad (3)$$

*Panel A: Regression results for Model 3 for US firms*

| | Adj. $R^2$ | Intercept | SAL | ΔARE | CGS | SAE | ΔAPA | ΔINV | ΔACP | OOE | DDA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Yearly Avg. | 48.38% | 0.035 | 0.729 | 0.452 | 0.726 | 0.724 | 0.449 | 0.457 | 0.461 | 0.711 | 0.702 |
| *t-statistic* | | 9.47 | 34.93 | 12.48 | 29.33 | 30.32 | 8.49 | 10.39 | 7.34 | 29.49 | 30.48 |
| *p-value* | | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0002* | *<.0001* | *<.0002* | *<.0001* | *<.0001* |
| | | | ΔOCL | ΔOCA | IED | IIN | ΔSTD | ITX | ΔITP | ΔDTX | C_OTHER |
| Yearly Avg. | | | 0.466 | 0.446 | 0.651 | 0.657 | 0.389 | 0.056 | 0.033 | 0.019 | 0.486 |
| *t-statistic* | | | 7.49 | 8.74 | 27.39 | 27.92 | 8.73 | 0.39 | 0.25 | 0.19 | 23.72 |
| *p-value* | | | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | 0.4739 | 0.3829 | 0.3982 | *<.0001* |
| *n = 22,512* | | | | | | | | | | | |

*Panel B: Regression results for Model 3for UK firms*

| | Adj. $R^2$ | Intercept | SAL | ΔARE | CGS | SAE | ΔAPA | ΔINV | ΔACP | OOE | DDA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Yearly Avg. | 42.49% | 0.023 | 0.576 | 0.351 | 0.572 | 0.562 | 0.348 | 0.357 | 0.351 | 0.568 | 0.562 |
| *t-statistic* | | 7.23 | 25.99 | 8.91 | 24.11 | 24.35 | 7.06 | 7.34 | 11.35 | 23.44 | 23.91 |
| *p-value* | | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* |
| | | | ΔOCL | ΔOCA | IED | IIN | ΔSTD | ITX | ΔITP | ΔDTX | C_OTHER |
| Yearly Avg. | | | 0.362 | 0.347 | 0.482 | 0.489 | 0.307 | 0.032 | 0.027 | 0.024 | 0.387 |
| *t-statistic* | | | 7.58 | 6.29 | 23.11 | 23.77 | 6.31 | 0.61 | 0.44 | 0.35 | 14.77 |
| *p-value* | | | *<.0001* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | 0.3411 | 0.2901 | 0.2893 | *<.0001* |
| *n = 4,958* | | | | | | | | | | | |

**Table V**.

Pair-wise test of differences in adjusted r-squares for Equations 1, 2, and 3 for both US and UK firms

| | US | | UK | |
|---|---|---|---|---|
| **Equation** | **2** | **3** | **2** | **3** |
| **1** | 9.17% | 13.88% | 5.95 % | 12.79% |
| | *9.9382* | *14.2894* | *8.3875* | *11.2855* |
| | <*.0001* | <*.0001* | <*.0001* | <*.0001* |
| **2** | | 4.71% | | 6.84% |
| | | *13.7712* | | *10.337* |
| | | <*.0001* | | <*.0001* |

**Notes:** We report the difference in adjusted R-square (in %), the t-statistic, and the p-value (italicised).

**Table VI**

Analysis of prediction errors

*Panel A*: Descriptive statistics of in-sample prediction error

| ***STATS*** | **\|*l(1)*\|** | **\|*l(2)*\|** | **\|*l(3)*\|** | **\|*l(2)*\| – \|*l(1)*\|** | **\|*l(3)*\| – \|*l(2)*\|** |
|---|---|---|---|---|---|
| *Mean* | 0.068 | 0.065 | 0.063 | –0.004 | –0.003 |
| *Std* | 0.078 | 0.074 | 0.071 | 0.028 | 0.014 |
| *Median* | 0.039 | 0.036 | 0.033 | –0.002 | –0.001 |
| *Min* | 0.000 | 0.000 | 0.000 | –0.312 | –0.185 |
| *Max* | 1.214 | 1.217 | 1.221 | 0.241 | 0.103 |

*Panel B*: Correlation analysis

| | **\|*l(1)*\|** | **\|*l(2)*\|** | **\|*l(3)*\|** | **\|*l(2)*\| – \|*l(1)*\|** | **\|*l(3)*\| – \|*l(2)*\|** |
|---|---|---|---|---|---|
| **\|*l(1)*\|** | | 0.922 | 0.906 | –0.303 | –0.136 |
| **\|*l(2)*\|** | 0.798 | | 0.98 | 0.083 | –0.160 |
| **\|*l(3)*\|** | 0.752 | 0.927 | | 0.075 | 0.036 |
| **\|*l(2)*\| – \|*l(1)*\|** | –0.380 | 0.148 | 0.133 | | –0.042 |
| **\|*l(3)*\| – \|*l(2)*\|** | –0.153 | –0.198 | 0.113 | –0.013 | |

**Notes:** In Panel A, |*l(n)*| represents in-sample prediction error from Equation (n) (see below). In Panel B, all coefficients are significant at the 5% level; the lower-left (upper-right) corner of Panel B reports average Spearman (Pearson) correlation coefficients.

**Table VII**
Out-of-sample prediction results

$$OCF_{t+1} = \propto + \beta_1 \sum CFO_t + \mu_t \quad (1)$$

$$OCF_{t+1} = \propto + \beta_1 C\_SALES_t + \beta_2 C\_COGS_t + \beta_3 C\_OE_t + \beta_4 C\_INT_t + \beta_5 C\_TAX_t + \beta_6 C\_OTHER_t + \mu_t \quad (2)$$

$$OCF_{t+1} = \propto + \beta_1 SAL_t + \beta_2 \Delta ARE_t + \beta_3 CGS_t + \beta_4 \beta_4 SAE_t + \beta_5 \Delta APA_t + \beta_6 \Delta INV_t + \beta_7 \Delta ACP_t + \beta_8 OOE_t + \beta_9 DDA_t + \beta_{10} \Delta OCL_t + \beta_{11} \Delta OCA_t + \beta_{12} IED_t + \beta_{13} IIN_t + \beta_{14} \Delta STD_t + \beta_{15} ITX_t + \beta_{16} \Delta ITP_t + \beta_{17} \Delta DTX_t + \beta_{18} C - OTHER_t + \mu_t \quad (3)$$

The absolute percentage forecast error:

$$APFE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{Actual\ CFO_t - Forecast\ CFO_t}{Actual\ CFO_t} \right|.$$

The symmetric mean absolute percentage error (SMAPE):

$$APFE = \frac{1}{n}\sum_{t=1}^{n} \frac{\left|Forecast\ CFO_t - Actual\ CFO_t\right|}{\left(\left|Actual\ CFO_t\right|\right) + \left(\left|Forecast\ CFO_t\right|\right)/2}$$

Theil's $U = \frac{\sqrt{\sum(\Delta \boldsymbol{P_t} - \Delta \boldsymbol{A_t})^2}}{\sqrt{\sum(\Delta \boldsymbol{A_t})^2}}$

*Panel A Out-of-sample prediction results for US firms*

| Median absolute percentage forecast error | | | Median paired forecast error difference | Median paired forecast error difference | Theil's U-statistic | Theil's U-statistic |
|---|---|---|---|---|---|---|
| Model 1 | Model 2 | Model 3 | Models 1 & 2 | Models 2 & 3 | Models 1 & 2 | Models 2 & 3 |
| 73.2% | 64.8% | 53.3% | 8.9%*** | 11.2%*** | 0.912 | 0.889 |

| Symmetric mean absolute percentage error | | | Symmetric mean paired error difference | Symmetric mean paired error difference |
|---|---|---|---|---|
| Model 1 | Model 2 | Model 3 | Models 1 & 2 | Models 2 & 3 |
| 42.3% | 38.7% | 31.2% | 3.6%*** | 7.5%*** |
| *n = 22,512* | | | | |

*Panel B Out-of-sample prediction results for UK firms*

| Median absolute percentage forecast error | | | Median paired forecast error difference | Median paired forecast error difference | Theil's U-statistic | Theil's U-statistic |
|---|---|---|---|---|---|---|
| Model 1 | Model 2 | Model 3 | Models 1 & 2 | Models 2 & 3 | Models 1 & 2 | Models 2 & 3 |
| 67.4% | 58.3% | 42.9% | 9.5%*** | 15.1%*** | 0.875 | 0.795 |
| Symmetric mean absolute percentage error | | | Symmetric mean paired error difference | Symmetric mean paired error difference | | |

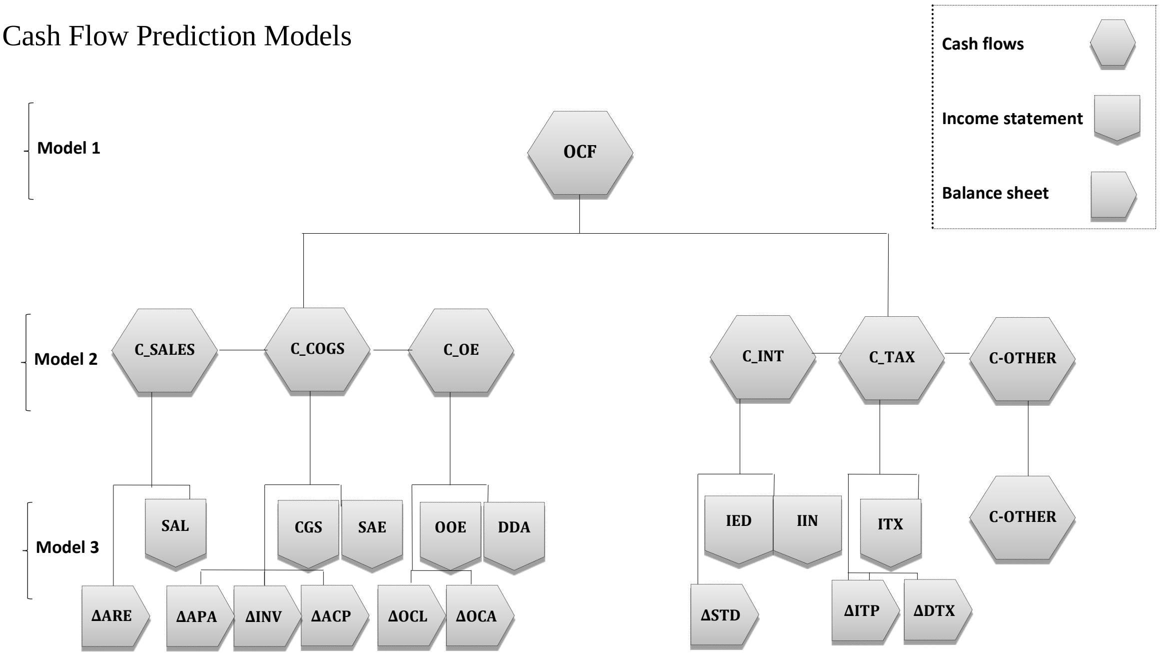
| Model 1 | Model 2 | Model 3 | Models 1 & 2 | Models 2 & 3 |
|---|---|---|---|---|
| 39.6% | 33.2% | 22.9% | 6.4%*** | 10.3%*** |
| *n = 4,958* | | | | |

*** indicates statistical significance at the 1% level or less.

## FIGURES

**Figure 1.**

Cash Flow Prediction Models




**Notes:**

OCF = Net cash flow from operating activities;
C_SALES = cash flows related to sales;
C_COGS = cash flows related to cost of goods sold;
C_OE = cash flows related to other operating expenses;
C_INT = cash flows related to interest;
C_TAX = cash flows related to tax;
C_OTHER = cash flows related to other revenue/expenses items;
SAL= sales;
ΔARE=changes in accounts receivable;
CGS=Cost of goods sold;
SAE=Selling and administrative expenses;
ΔAPA= changes in Accounts payable;
ΔINV=changes in inventories;
ΔACP=changes in Accrued payroll;
OOE=other operating expenses;
DDA=depreciation, depletion, and amortisation;
ΔOCL= changes in other current liabilities;
ΔOCA=changes in other current assets;
IED=interest expense on debt;
IIN= interest income;
ΔSTD=changes in short term debt;
ITX= income tax;
ΔITP=changes in income tax payable;
ΔDTX=changes in deferred tax.