Do Core and Non-Core Cash Flows from Operations Persist Differentially in Predicting Future Cash Flows? Analyses Based Upon Industry Membership

SYED K. ZAIDI, *PhD, MBA, CMA, CFE, DCS*
Associate Professor of Accounting
Department of Accounting and Business Law
College of Busiess
Louisiana State University Shreveport
One University Place
Shreveport, LA 71115
syed.zaidi@lsus.edu

VERONICA PAZ, *DBA, CPA, CITP, CFF, CGMA*
Professor of Accounting
Department of Accounting
Elberly College of Business and Information Technology
Indiana University of Pennsylvania
664 Pratt Drive
Indiana, PA 15705, USA
vpaz@iup.edu

Abstract

This paper replicates and extends Cheng and Hollie (2008; hereafter referred to CH) research by examining the influence of industry membership on the fit of the CH disaggregated future cash flow prediction model. This study is built upon Barth et al. (2001). CH provides empirical support that a disaggregated cash flow model can improve future cash flows' predictability one year ahead. CH finds that core components of cash flows (i.e., cash flows related to sales, cost of goods sold, and operating expenses) have greater persistence than non-core cash flows (i.e., cash flows related to interest expenses, tax payments, etc.). The current research replicates and extends the CH study for an extended sample period 1988-2010. The replication findings suggest that different core and non-core components of cash flows have different persistence levels. However, they do not support that core cash flows have higher persistence than non-core cash flows in predicting one year ahead in sample cash flows. In addition, the findings suggest that industry membership significantly affects the fit of the disaggregated cash flow prediction model of CH. As such, industry membership plays an important role in predicting the fit of the CH model across different industries.

Key words: Accounting, Finance, Disaggregated Future Cash Flow Prediction Model, Core and Non-Core Cash Flows

Introduction

Cash flows have different persistence from earnings in predicting future cash flows (Finger, 1994; Sloan, 1996; Burgstahler et al., 1998). CH extend the findings of Barth et al. (2001) by examining the role of cash flows in predicting future cash flows. They disaggregate cash flows from operations into core and non-core cash components and conclude that core cash flows have higher persistence than non-core cash flows in predicting future cash flows. This paper replicates and extends CH research by examining the impact of industry membership on persistence levels of core and non-core components of cash flows in predicting one year ahead future cash flows. The present research follows CH in defining what constitutes core and non-core cash flows. Core cash flows are those cash flows that are related to sales, cost of goods sold (COGS), and operating expenses (OE). Non-core cash flows are cash flows associated with payment of interest expenses, taxes, and other revenue/expense items such as extraordinary items.

This research uses Compustat data from 1988 to 2010 with a total of 29,612 observations in the final sample. The adjusted R^2 suggests that the disaggregated cash flow model explains 33% of variation in the one year ahead future cash flows. This paper also conducts pairwise comparisons to investigate the persistence levels of different components of core and non-core cash flows. The results indicate that different components of core and non-core cash flows persist differently in predicting future cash flows.

Firms differ in their composition and levels of core and non-core cash flows. Therefore, understanding persistence levels of core and non-core cash components at industry level may have important implications for investors and financial analysts. Following Barth et al. (1998), the current research conducts industry level analyses for 13 industries (excluding financial services). The findings suggest that industry membership influences the fit of the CH disaggregated cash flow prediction model. The adjusted R^2 value of 0.62 suggests that disaggregated CH model works best for the transportation sector.

Literature Review

Extant literature supports the ability of cash flows to predict future cash flows (Finger, 1994; Sloan, 1996; Burgstahler et al., 1998; Barth et al., 2001). Barth et al. (2001) suggest that cash flow is a primary valuation construct that requires estimation for valuing a firm and/or its assets. DeFond and Hung (2003) state that market participants (i.e., investors and financial analysts) are increasingly requiring firms to report predicted future cash flows for making assessments of firm value and stock price.

Extant literature recommends disaggregation of cash flows into core and non-core cash components. American Institute of Certified Public Accountants (AICPA) recommends firms to distinguish between the financial effects of their core (major or central operations) and non-core (peripheral or incidental activities) cash flows so that the analysts have an in-depth information of firms' financial health. A firm's ability to generate operating cash flows (hereafter referred to CFO) and operating earnings is closely linked to a firm's value; therefore, the primary objective of financial reporting is to provide useful information to help analysts assess the amount and timing of prospective cash flows and earnings (FASB, 1978).

Understanding the impact of cash flows and predicting future cash flows are both academically and practically relevant. This paper replicates CH by estimating cross-sectional disaggregated cash flow prediction model for the sample period 1988-2010. However, CH do not evaluate the fit of their model at the industry level. Therefore, the current research also contributes to the accounting literature by conducting industry-level analyses to validate the fit of the CH model across different industries.

Lev et al. (2010) provide evidence that industry membership influences research findings. Portfolio managers, whether managing institutional or individual investors, invest in portfolios of assets based on investors' risk preferences and securities' risk-return characteristics. Similarly, some hedge funds invest in portfolios based on industry sectors such as utilities. As a result, portfolio managers and/or individual investors may choose to include only a few sectors (utilities, computers, etc.) in their investment portfolios. Therefore, this paper groups firms into portfolios based on industry membership to analyze the persistence of predictive ability of disaggregated cash flow models at an industry level.

Specifically, this paper compares the adjusted R^2 among different industries and the adjusted R^2 of each industry (nested model) with the cross-sectional model (full model) to evaluate the validity of the CH model across different industries. If the CH model has a different predictive ability for different industries, investors would be able to enhance the value of their portfolios by longing those industries that CH model provides the best fit for. Similarly, investors would also be able to enhance their portfolios' value by shorting those industries that CH model explains the least.

Hypothesis Development

CH examine whether different components of cash flows (i.e., core and non-core cash flows) have different persistence levels in predicting future cash flows. This research replicates CH research by increasing the sample period to 23 years from 1988 to 2010.

CH states that the core cash flows have greater persistence than non-core cash flows. Market and firm specific factors such as firms' financing and investment policy affect non-core cash flows, and therefore, non-core cash flows are less stable (Arthur et al., 2010). Consequently, as a part of the replication of the CH study, this paper develops the following hypotheses relating to the persistence of core and non-core components of cash flows.

H1: The persistence levels of different cash (core and non-core) flow components differ significantly.

Extant literature documents the importance of estimating regression models at the industry level (Barth et al., 2001; Lev et al., 2010). Lev et al. (2010) examine the influence of accounting estimates on cash flow and earnings predictions at industry level. The authors find different results for some industries. The authors find that for some industries (oil and gas, printing and publishing, and eating and drinking places), accounting estimates do not improve cash flow predictions beyond the predictions based on CFO only. Barth et al. (2001) suggest that substantial industry-level variation exists in the cash flows and earnings. However, extant literature does not provide explanations on whether a disaggregated cash flow prediction model fits similarly or differently across different industries. Hence, this paper develops the following hypothesis:

H2: Industry membership affects the fit of disaggregated cash flow prediction (i.e. CH model) model.

Research Design

This paper replicates and extends CH by examining the impact of core and non-core cash flows on cash flow predictions based on regression models that group sample firms according to their industry membership. One purpose of this study is to replicate CH study by including the firms in the sample for the period from 1988 to 2010. Following CH study, the disaggregated cash flow prediction model is as follows:

$$CFO_{t+1} = \beta 0 + \beta 1 * \Sigma ACC_t + \beta 2 * C\_SALES + \beta 3 * C\_COGS + \beta 4 * C\_OE + \beta 5 * C\_INT + \beta 6 * C\_TAX + \beta 7 * C\_OTHER + \varepsilon$$

Consistent with CH research, core cash flows include cash flows related to sales, cost of goods sold, and operating expenses. Non-core cash flows include cash flows related to interest and tax expenses. To ensure comparability with CH, this paper defines the following variables as:

ACC = sum of accruals
C_SALES = cash flows from sales are calculated as sales (#12) minus change in accounts receivable – trade (#151)
C_COGS = cash flow from cost of goods sold is calculated as cost of goods sold (#41) minus [change in inventory (#3) minus change in accounts payable (#70)]
C_OE = cash flow from operating and administrative expenses are calculated as operating expenses1 minus change in Net Operating Working Capital excluding changes in accounts receivable-trade, inventory, tax payable, and interest payable
C_INT = cash flow related to interest payment (#315)
C_TAX = cash flow related to tax payments (#317)
C_OTHER = cash flows related to other revenue/expenses items including special and extraordinary items are calculated as cash flow from operations (#308) minus all other cash flow components (i.e., cash flows related to sales, COGS, operating expenses, interest, and taxes).

Industry Analysis

This research examines the impact of industry membership on overall fit of the cross-sectional model across different industries. Firms are grouped into different portfolios based upon industry-membership. Following Barth et al. (1998, 2001), this study estimates the disaggregated cash flow predictions model for 13 industries. Primary SIC codes determine industry membership as follows: Agriculture (0100 – 0999), Mining+Construction (1000 – 1999, excluding 1300 – 1399), Food (2000 – 2111), Textiles+Printing/Publishing (2200 – 2780), Chemicals (2800 – 2824, 2840 – 2899), Pharmaceuticals (2830 – 2836), Extractive (2900 – 2999, 1300 – 1399), Durable Manufacturers (3000 – 3999, excluding 3570 – 3579 and 3670 – 3679), Computers (7370 – 7379, 3570 – 3579, 3670 – 3679), Transportation (4000 – 4899), Utilities (4900 – 4999), Retail (5000 – 5999), and Services (7000 – 8999, excluding 7370 – 7379).

Industry Specific Regressions

This research estimates annual regression models for each of the 13 industries in the sample. Using F-tests (ANOVA), this study compares the R^2 of all industries to test the null hypothesis "the mean adjusted R^2 of different industries are same" against the alternative hypothesis "the mean adjusted R^2 of at least one industry differs from those of other industries." In addition, this research conducts t-tests to examine if the adjusted R^2s differ significantly among different industries. This shall provide insights about the predicative ability of generic model versus industry-specific disaggregated cash flows predictions model.

Data and Findings

This study obtains data from the 2010 Compustat Annual Industrial, Research, and Full Coverage files. The sample period 1988-2010 allows 258,164 initial observations. To ensure comparability with the CH study, this research uses the same criterion for getting the final sample. Specifically, this research excludes financial services firms (SIC codes 6000-6999; 61,949 observations), because the CH future cash flow prediction model does not reflect their activities. This research also excludes observations with sales less than $10 million and share price less than $1 (85,829 observations) as well as missing data (79,434 observations). Finally, this study also excludes the extreme values for earnings and cash flows that are in the top and bottom 1% of the data. The final sample includes 29,612 observations. This study scales down all the variables by average total assets. Table 1 reports the data collection process of this research.

Table 1. Sample Description

Items	Firm Years
Total Number of Observations from Compustat (1988--2010)	258,164
Less Observations from the financial services industry (SIC 6000-6999)	(61,949)
Less Observations for sales value less than $10 million, Share price $1	(85,829)
Less Observations for missing data	(79,434)
Less trimming of Earnings and CFO at the top and bottom 1%	(1,340)
Final Sample (firm years)	29,612

Table 2 provides description of industries in the sample. The sample contains observations from 13 industries (excluding financial services) as suggested by Barth et al. (1998). The largest number of observations in the sample is within Durable Manufacturers. This represents about 27% of the sample followed by approximately 14% observations in each of the Retail and Computers sectors. The least number of observations are in the Agriculture sector with a total of only 131 observations for a total of less than 1% of the overall sample. Other industry membership includes Transportation (6.8%), Services (8.6%), Extractive (6.3%), and Food (3.4%). The description of industries in the sample is provided below.

Table 2. Number of Observations in each Industry

Industry	Observations
Agriculture	131
Mining+Construction	802
Food	1,001
Textiles+Printing/Publishing	2,118
Chemicals	997
Pharmaceuticals	899
Extractive	1,869
Durable Manufacturers	7,873
Computers	4,014
Transportation	2,014
Utilities	1,147
Retail	4,071
Services	2,551
Others	125
Total	29,612

Table 3 provides descriptive statistics for the sample in the study. The number of observations in the current study is 29,612 as compared to 29,010 observations in CH. The mean associated with CFO is .088, which is greater than the mean CFO (.059) reported in CH. The mean cash flows associated with sales, cost of goods sold, operating expenses, interest expenses, taxes, and others are 1.11, .825, .121, .017, .022, and -.037, respectively. Specifically, the mean cash flows associated with sales, operating expenses, interest, and tax expenses are slightly lower than those reported in CH.

Table 3. Descriptive Statistics

STATS	CFO	C_SALES	C_COGS	C_OE	C_INT	C_TAX	C_OTHER
Mean	0.088	1.111	.825	.121	.017	.022	-.037
Std	.093	.846	0.647	.813	.280	.0183	.322
Median	.089	.911	.609	.0664	.013	.013	0.009
N	29,612	29,612	29,612	29,612	29,612	29,612	29,612

Cash flows associated with C_COGS, C_OE, C_INT, and C_TAX represent cash outflows.

The upper right (lower left) portion of the Table 4 reports Spearman and Pearson correlation coefficients, respectively. Consistent with CH, the correlation between cash flows associated with sales (C_Sales) and COGS (C_COGS) is very high at .87 for Spearman correlation (.92 for Pearson correlation, p-value <.001). Also, the correlation between C_sales and C_Tax (cash paid for taxes) is .25 for Spearman correlation and .18 for Pearson Correlation.

Table 4. Spearman and Pearson Correlation Coefficients, N = 29612

	CFO	ACC	C_SALES	C_COGS	C_OE	C_INT	C_TAX	C_OTHER
CFO	1.00	-.487	.0632	-.0142*	.173	-.146	.336	.252
ACC	-.445	1.00	.088	.058	-.228	-.055	.219	-.372
C_SALES	.023	.097	1.00	.087	.136	-.019	.245	-.219
C_COGS	-.035	.070	.920	1.00	-.041	.062	.136	-.007^
C_OE	.146	-.230	.200	.008^	1.00	-.213	.036	.402
C_INT	-.121	-.056	-.019	.001^	-.118	1.00	-.224	-.063
C_TAX	.301	.216	.184	.080	.056	-.211	1.00	-.0925
C_Other	.271	-.369	-.107	.123	.380	-.042	-.079	1.00

The numbers on the upper right (lower left) of the diagonal represent Spearman and Pearson correlation coefficients, respectively. ^insignificant at 0.05; *insignificant at .01; all others are significant at 0.01

Table 5 provides regression results for the cross-sectional model in this research. The adjusted R^2 is .33, which is slightly less than the adjusted R^2 of .39 in the CH study. Therefore, dependent variables in the current study explain 33% of the variation in one year-ahead cash flows. For core components of cash flows, the estimated regression coefficients for cash flows associated with sales, cost of goods sold, and operating expenses are .50, -.51, and .49, respectively. Regression coefficients related to non-core cash flows for interest expense, tax payments, and other revenue/expense items are -.75, .012, and .52, respectively. The regression coefficient for accruals is .13. All the variables, except C_Tax, are statistically significant at p-value <.0001.

Table 5. Regression Model-Future Cash Flow on Current Cash Flow and Accrual Components

$CFO_{t+1} = \beta 0 + \beta 1{*}\Sigma ACC_t + \beta 2{*}C\_SALES + \beta 3{*}C\_COGS + \beta 4{*}C\_OE + \beta 5{*}C\_INT + \beta 6{*}C\_TAX + \beta 7{*}C\_OTHER + \varepsilon$

R^2	0.33
Adjusted R^2	0.33
Root MSE	0.07
Denominator DF	29,611.00

Parameter	Estimate	Standard Error	t-value	Pr > |t|
Intercept	.051	.001	43.03	<.0001
C_Sales	.504	.008	60.22	<.0001
C_COGS	-.512	.008	-61.38	<.0001
C_OE	-.494	.008	-56.77	<.0001
C_INT	-.755	.030	-24.88	<.0001
C_TAX*	.012	.027	.44	.6616
C_OTHER	.524	.008	63.52	<.0001
ACC	.130	.008	16.35	<.0001

*insignificant at 0.05; all others are significant at p-value < .0001

In order to test the persistence of different components of core and non-core cash flows, this study conducts several paired t-tests. This research estimates regression coefficients for each component of cash flow for each sample year and conducts paired t-tests to evaluate if different components persist differently in predicting future cash flows. Specifically, this study compares the mean coefficients from the yearly regressions using Fama-MacBeth statistics (Fama and MacBeth, 1973). This approach is consistent with the CH study.

Table 6 provides results of paired t-tests between different components of core and non-core cash flows. All paired t-tests except between C_sales and C_other are statistically significant at p-value <.0001. Paired t-test between

C_sales and C_other is significant at p-value <.05. This supports H1 that different components of core and non-core cash flows have different persistence levels. However, the findings are not consistent with the CH study. CH finds that core cash flows (i.e., C_Sales, C_COGS, and C_OE) have higher persistence than non-core Cash flows (C_INT, C_TAX, and C_Others) in predicting one year ahead future cash flows. This study expects this difference owing to different sample periods.

Table 6. Test of Differences in Coefficients of Variables in Regression

Variable	C_COGS	C_OE	C_INT	C_TAX	C_OTHER
C_Sales	<.0001 (-8.98)	<.0001 (-8.99)	<.0001 (-10.8)	<.0001 (-8.52)	<.05 (2.36)
C_COGS		<.0001 (-4.83)	<.0001 (-5.69)	<.0001 (-9.13)	<.0001 (-9.01)
C_OE			<.0001 (-5.35)	<.0001 (-9.17)	<.0001 (-9.03)
C_INT				<.0001 (10.47)	<.0001 (-10.75)
C_Tax					<.0001 (8.69)

P-value is reported along t-statistic in brackets for each pair-wise comparison.
All are significant at p <.05

This paper extends CH research by conducting industry analyses. Industry membership affects research findings (Lev et al., 2010). Industry analyses provide evidence that the fit of CH disaggregated cash flow prediction model varies across industries. This paper employs Barth et al. (1998) 13 industry classification for conducting industry analyses. Table 7 reports the overall comparison of means (ANOVA) of the adjusted R^2s of 13 industries in the model. The ANOVA results provide that the overall model is significant at p-value <.001. This suggests that means of adjusted R^2s of at least two industries are different.

Table 7. Overall Comparison of Means of Adjusted R^2 of Industries in the Model

Source	DF	Sum of Squares	Mean Squares	F-Value	Pr>F
Model	12	1.834	.152	8.17	<.0001
Error	246	4.600	.019		
Corrected Total	258	6.434			

Dependent variable: Adjusted R^2
Number of industries in the model: 13
The model is significant at p-value <.001

In order to further investigate adjusted R^2s industries that are different from the overall cross sectional adjusted R^2, this study performs additional analyses. One sample t-tests compares the mean of yearly adjusted R^2s of each industry against the cross-sectional adjusted R^2 of .33 (see Table 5). Table 8 reports industry names, observations in each industry, average adjusted R^2s of each industry, overall cross sectional adjusted R^2, differences between the average adjusted R^2 and cross sectional adjusted R^2, and p-values. The findings show that the average adjusted R^2 of all industries (excluding Durable Manufacturers, Computers, and Retail sectors) are significantly different from the overall cross-section adjusted R^2 at 1%, 5%, or 10% levels.

The average adjusted R^2 (0.62) of the Transportation sector is much higher than the cross sectional adjusted R^2 (.33). Moreover, this difference is statistically significant at p-value <.001. This suggests that CH disaggregated future cash flow prediction model fits much better for the Transportation sector than any other sector. Thus, industry membership impacts the fit of disaggregated future cash flow prediction model developed in the CH study. Hence, this study finds partial support for H2.

Table 8. Comparison of Single Industry Adjusted R^2 with the Cross-Sectional Adjusted R^2

Industry	N	Average Adjusted R^2	Overall Adjusted R^2	Difference	p-value
Agriculture	4		0.3302		
Mining+Construction	21	0.3803	0.3302	0.0501	0.093*
Food	21	0.4511	0.3302	0.1209	0.0003**
Textiles+Printing/Publishing	22	0.3903	0.3302	0.0601	0.089*
Chemicals	21	0.4462	0.3302	0.116	0.0011**
Pharmaceuticals	21	0.502	0.3302	0.1718	<.0001***
Extractive	21	0.389	0.3302	0.0588	0.055*
Durable Manufacturers	22	0.3143	0.3302	-0.0159	0.58
Computers	21	0.3149	0.3302	-0.0153	0.4386
Transportation	21	0.6194	0.3302	0.2892	<.0001***
Utilities	21	0.4331	0.3302	0.1029	0.0395**
Retail	22	0.3148	0.3302	-0.0154	0.4746
Services	21	0.3945	0.3302	0.0643	.015**

*** significant at 1%; ** significant at 5%; *significant at 10%

Finally, this study also conducts several paired t-tests to examine whether the adjusted R^2s of two industries differ. Appendix A provides results of several paired t-tests. A paired t-test of average adjusted R^2s between Chemical and Retail or Chemicals and Transportation are significant at 1%. This suggests that the average adjusted R^2 of Chemicals sector differ significantly from the average adjusted R^2s of the Transportation and Retail sectors. As such, there are significant differences in the adjusted R^2s for several pairs of industries. Hence, the disaggregated CH model fits differently for different industries. This information is helpful for financial analysts and investors in deciding the industries that should be included in their investment portfolios.

Since a cross-sectional model is only good for those investors who completely diversify their portfolios, industry-wise analyses are important to consider for making better predictions about risk and return characteristics of less than fully diversified portfolios based on the future cash flow estimates.

Robustness Check

This study also conducts robustness tests to analyze the validity of findings. Specifically, this research estimates the regression model after deleting all missing values for changes in accounts receivables and accounts payables. The sample size for this analysis is 20,291 observations. Table 9 presents the regression results and provides support for the robustness of the research findings. Consistent with the findings (see Table 5), all variables except cash flows associated with taxes (C_tax) are significant at p-value <.0001.

Table 9. Robustness Check

R2	0.33
Adjusted R2	0.33
Root MSE	0.073
Denominator DF	20.290

Parameter	Estimate	Standard Error	t-value	Pr > |t|
Intercept	.050	.001	34.76	<.0001
C_Sales	.51	.009	50.94	<.0001
C_COGS	-.51	.009	-51.81	<.0001
C_OE	-.50	.010	-48.06	<.0001
C_INT	-.75	.037	-20.18	<.0001
C_TAX*	-.01	.032	-.29	.7701
C_OTHER	.53	.010	53.77	<.0001
ACC	.12	.009	12.67	<.0001

*insignificant at 0.05; all others are significant at p-value <.0001

Discussion

AICPA recommends that firms should distinguish between their core and non-core operations to better assist investors in evaluating financial statements. CH provides support to the AICPA's objective and finds that core cash flows have higher persistence than non-core cash flows in predicting future cash flows. The purpose of the current research is to replicate and extend CH study by conducting the industry-wise analyses. The findings suggest that different components of core and non-core cash flows persist differently in predicting one year ahead future cash flows.

This study also conducts industry analyses to understand the impact of industry membership on the fit of disaggregated cash flow model across different sectors. The results partially support H2, which suggest that the fit of the cross-sectional model differs significantly across different industries. Specifically, the transportation sector fits best into the model with an adjusted R2 of .62. Therefore, CH model fits differently across different sectors.

The findings of current research are relevant to both accounting literature and practice. The accounting researchers can build upon this research to develop more sophisticated industry-wise disaggregated cash flow prediction models. Financial statements users (such as investors, portfolio managers, etc.) can gain valuable insights from the findings and use the model to make predictions about firm value and stock price.

Future researchers could divide the sample firms into different portfolios based on their size (i.e. total assets or sales) and examine the impact of size on the model fit. Baginski et al. (1999) states that firm specific characteristics (such as capital intensity, firm size, etc.) cause firm earnings to behave in specific persistent manners with respect to those characteristics. The authors state that firm size may also affect earnings persistence because larger firms are well diversified and have more stable growth than smaller firms. Scherer (1973) shows that larger firms have greater financial resources and they use these resources to diversify with an aim to attain sustained and stable long-term growth. As such, size may have an impact on research findings, and therefore, future research can be conducted to explore this issue.

References

American Institute of Certified Public Accountants (1994). *Special report of the special committee on financial reporting: meeting the information needs of investors and creditors.*

Arthur, N., Cheng, M., Czernkowski, R. (2010). *Cash flow disaggregation and the prediction of future earnings*, Accounting and Finance, Vol. 50, no. 1, pp. 1-30.

Baginski, S., Lorek, K., Willinger, G., Branson, B. (1999). *The relationship between economic characteristics and alternative annual earnings persistence measures*, The Accounting Review, Vol. 74, pp. 105-120.

Barth, M., Beaver, W., Landsman, W. (1998). *Relative valuation roles of equity book value and net income as a function of financial health*, Journal of Accounting and Economics, Vol. 25, pp. 1-34.

Barth M. E., Cram D., Nelson K. (2001). *Accruals and the prediction of future cash flows*, The Accounting Review, Vol. 76, pp. 27-58.

Burgstahler D., Jiambalvo J., Pyo Y. (1998). *The informativeness of cash flows for future cash flows*, University of Washington, working paper.

Cheng, C. A., Hollie, D. (2008). *Do core and non-core cash flows from operations persist differently in predicting future cash flows?*, Review of Quantitative Finance and Accounting, Vol. 31, no. 1, pp. 29-53.

DeFond M., Hung M. (2003). *An empirical analysis of analysts' cash flow forecasts*, Journal of Accounting and Economics, Vol. 35, pp. 73-100.

Fama E. F., MacBeth J. D. (1973). *Risk, return, and equilibrium: empirical tests*, Journal of Political Economy, Vol. 81, pp. 607-636.

FASB (1978). *Statement of financial accounting concepts No. 1: objectives of financial reporting by business enterprises*, FASB, Stamford, CT.

Finger C. (1994). *The ability of earnings to predict future earnings and cash flow*, Journal of Accounting Research, Vol. 32, pp. 210-223.

Lev, B., Li, S., Sougiannis, T. (2010). *The usefulness of accounting estimates for predicting cash flows and earnings*, Review of Accounting Studies,Vol. 15, pp. 779-807.

Scherer, F. M. (1973). *Industrial Market Structure and Economic Performance*, Chicago, IL: Rand McNally.

Sloan R. (1996). *Do stock prices fully reflect information in accruals and cash flows about future earnings?*, The Accounting Review, Vol. 71, pp. 289-315.

Appendix A

A Pair-wise Comparisons between Adjusted R^2 of Two Industries

Industry	1	2	3	4	5	6	7	8	9	10	11	12	13	N
Average	.5	.38	.45	.39	.47	.5	.38	.31	.31	.62	.43	.31	.39	
SD	.24	.12	.15	.14	.14	.13	.13	.13	.09	.08	.21	.1	.11	
1	.	.	.	.	.	.	.	.	.	.	.	.	.	4
2			-.708 (-1.92, .0694)*	.0139 (.34, .734)	-.0659 (-1.90, .0713)*	-.122 (-3.52, .002)***	-.008 (-.28, .784)	.09 (2.70, .0138)***	.0654 (2.31, .0318)***	-.24 (-7.42, <.0001)***	-.0528 (-1, .33)	.062 (1.93, .068)*	-.014 (-.46, .64)	20
3				.0847 (2.51, .021)**	.004 (.18, .85)	-.051 (-1.21, .24)	.062 (1.58, .13)	.16 (4.51, .0002)***	.137 (3.67, .002)***	-.17 (-5.10, <.0001)***	.018 (.33, .75)	.133 (3.73, .001)**	.057 (1.56, .1349)	20
4					-.798 (-2.22, .038)**	-.135 (-3.42, .002)**	-.22 (-.53, .60)	.076 (2.77, .011)**	.051 (1.41, .17)	-.253 (-9.60, <.0001)***	-.067 (-1.13, .27)	.076 (1.99, .059)**	-.029 (-.72,.48)	21
5						-.056 (-1.24, .228)	.057 (1.39, .179)	.15 (4.11. .0005)***	.13(3.61, .0017)**	-.173 (-4.94, <.0001)***	.013 (.23, .82)	.12 (4.03, .0007)***	.052 (1.74, .098)*	20
6							.11 (3.56, .002)**	.213 (6.87, <.0001)***	.18 (5.93, <.0001)***	-.117 (-3.08, .006)**	.069 (1.17, .25)	.18 (5.69, <.0001)***	.107 (2.96, .008)**	20
7								.10 (3.38, .003)**	.074 (2.91, .009)**	-.23 (-.682, <.0001)***	-.044 (-1.05, .30)	.07 (2.53, .020)**	-.005 (-.15,.88)	20
8									-.026 (-1.13, .27)	-.33 (-14.34, <.0001)***	-.14 (-3.04, .006)*	.000 (-.01,.98)	-.10 (-.3.41, .003)**	21
9										-.305 (-10.43, <.0001)***	-.119 (-2.67, .015)**	-.003 (-.14,.89)	-.08 (-3.38, .003)**	20
10											.18(3.55, .002)**	.30 (11.10, <.0001)***	.225 (7.48, <.001)***	20
11												.115 (2.58, .018)**	.038 (.75,.45)	20
12													-.077 (-2.64, .016)**	21
13														20

Industries: 1-Agriculture, 2-Mining+Construction, 3-Food, 4-Textiles+Printing/Publishing, 5-Chemicals, 6-Pharmaceuticals, 7-Extractive, 8-Durable Manufacturers, 9-Computers, 10-Transportation, 11-Utilities, 12-Retail, and 13-Services; ***significant at 2%; **significant at 5%; *significant at 10%