The Pennsylvania State University

The Graduate School

The Mary Jean and Frank P. Smeal College of Business Administration

THE INCREMENTAL CASH FLOW PREDICTIVE ABILITY OF ACCRUAL MODELS

A Thesis in

Business Administration

by

Timothy R. Yoder

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

August 2006

UMI Number: 3231920

ProQuest Information and Learning Company
300 North Zeeb Road
P.O. Box 1346
Ann Arbor, MI 48106-1346

The thesis of Timothy R. Yoder was reviewed and approved* by the following:

Dan Givoly
Ernst & Young Professor of Accounting
Department Chair
Thesis Advisor
Chair of Committee

James McKeown
The Mary Jean and Frank P. Smeal Chaired Professor of Accounting

Orie Barron
Associate Professor of Accounting

N. Edward Coulson
Professor of Economics

*Signatures are on file in the Graduate School

Abstract:

Prior studies on the incremental predictive ability of accrual models over cash flow models with respect to future cash flows led to conflicting results. This paper extends the model of the accrual process developed by Barth, Cram, and Nelson (2001) by including cash flow implications of growth in future sales. The Barth, Cram, and Nelson model is further modified to allow the incorporation of accrual-based prediction of future sales. This paper also presents an accrual-based cash flow prediction model based on a random walk in cash flows adjusted for the reversal of current payables and receivables. Initial results indicate that this simple model based on the complete reversal of current payables and receivables predicts future cash flows better than models based on current cash flows alone. No initial evidence is found that the more sophisticated accrual-based prediction model developed in this paper and estimated via WLS has incremental predictive power beyond that of the accrual reversal model or the cash flow-based models. However, supplementary analysis using a more powerful estimation procedure where the prior three years of observations are pooled does find that the accrual-based WLS model dominates both the cash flow-based models and the accrual reversal model. Consistent with accruals incorporating predictions of future sales, the paper finds that the accrual-based WLS model (when estimated while pooling the prior three years data) is superior to the cash flow-based model in capturing the effect of future sales on future cash flows. In fact, for 13 of 17 industries, tests cannot detect a decrease in absolute forecast errors when actual sales are substituted for expected sales in the accrual-based prediction model.

TABLE OF CONTENTS

LIST OF TABLES

ACKNOWLEDGEMENTS

I wish to thank the members of my dissertation committee for their support and guidance throughout this project: Dan Givoly (chair), Jim McKeown, Orie Barron and Ed Coulson. Discussions with fellow PhD students Santhosh Ramalingegowda, Yong Yu, Hal White, and Shelley Curling were invaluable to the completion of this paper. Nothing would ever get accomplished if not for the hard work of the accounting department's administrative support team. Tammy Snook, Linda Roan, and Cynthia MannellaNickell work tirelessly to ensure the graduate students in the accounting department have everything they need to succeed. Finally, this paper benefited greatly from comments received at presentations to the following universities: University of Arizona, University of Cincinnati, University of Oklahoma, University of Illinois at Chicago, Oregon State University, Mississippi State University, Florida International University and Southern Methodist University.

My network of family and friends has provided me wonderful personal support throughout my five and a half years at Penn State. My lovely bride, Sally Flowers, has never let me doubt myself and helped me focus on each step in the long dissertation process. Sally and her three-year-old daughter, Hazel, have taught me what is important in life and I look forward with incredible excitement to the new life we will soon be starting! My officemate and dear friend Shelley Curling has always been there to listen. The benefit of having a friend that understands what you are going through (because she is going through the same) is immeasurable. Never underestimate the power of a discussion over beer at the Sports Café with a good friend to calm your nerves and get you back on track! Finally, I wish to thank my parents, Ezra and Alice, for their incredible support. They never questioned my decision to give up a career in public accounting to become (once again) a student. Though they grew up in a culture that did not value higher education, they stressed to me the importance of education from a very early age. Their attitude towards education helped fuel my own passion for education that has led me down the road to earning my PhD. Thanks Mom and Dad.

1. Introduction

Financial reporting should enable financial statement users to produce more accurate cash flow forecasts. According to the Financial Accounting Standards Board (FASB 1978, page 5):

. . .financial reporting should provide information to help investors, creditors, and others assess the amounts, timing, and uncertainty of prospective net cash inflows to the related enterprise.

Accrual accounting is one component of financial reporting that should assist in cash flow predictions (FASB 1978, page 5):

Information about enterprise earnings based on accrual accounting generally provides a better indication of an enterprise's present and continuing ability to generate favorable cash flows than information limited to the financial effect of cash receipts and payments.

The implication of the FASB's statement of concepts is that accruals[1] should have incremental predictive ability beyond that of current cash flows in predicting future cash flows.[2]

The FASB does not specifically address the time period over which future cash flows should be predicted. Although financial statement users are likely interested in

---

[1] "Accruals" cannot, by themselves, predict future cash flows. Financial statement variables (i.e. cash flows, accruals, and inventory) are used in prediction models, which in turn produce cash flow forecasts. This is an important distinction as any finding regarding incremental predictive ability is a finding regarding the prediction model used, not the financial statement variables themselves. However, it is less cumbersome to discuss the predictive ability of financial statement variables. Any mention of the predictive ability of financial statement variables in this paper refers to the predictive ability of the prediction model being applied.

[2] Two popular measures of cash flows are cash flows from operations and free cash flows, defined as cash flow from operations less dividend payments and investments in property, plant, and equipment. In SFAC No. 1, paragraph 37, FASB states that financial reporting should provide information to investors about " . . .an enterprise's ability to generate enough cash to meet its obligations when due and its other cash operating needs, to reinvest in operations, and to pay cash dividends . . ." (FASB 1978). FASB's reference to free cash flows is supported by the use of that measure by most valuation models. Since there is no clear theory linking accruals to either future dividend payments or future capital expenditures, this paper investigates the incremental predictive ability of accrual models for future operating cash flow. Since operating cash flow is the major component of free cash flow, an improved prediction of operating cash flow should result in an improved prediction of free cash flow.

long-term cash flows, there is anecdotal evidence that investors are also concerned with current and short-term predictions of cash flows. Frederick Taylor, while chairman of the investment policy committee at U.S. Trust Co. stated, “Earnings are very important, but if cash flow is improving, we will buy a stock where earnings have been going nowhere.” (Dreyfus 1988, page 56.) Short-term cash flow predictions could provide information to investors on the trend in cash flows. As additional anecdotal evidence of investors’ concern with cash flows, a 1999 survey by *Institutional Investor* found that 51% of chief financial officers reported analysts and institutional investors were placing more emphasis on cash flow analysis than in the prior two years.

Firm stakeholders other than equity investors may also be interested in short-term cash flows. Potential vendors to the firm may be interested in a firm’s ability to pay before entering large contracts. Creditors may be interested in a firm’s short-term cash flows in making lending or debt restructuring decisions. Employees and prospective employees may be interested in whether the firm can meet its payroll obligations. This study investigates whether accruals possess one particular useful characteristic: the ability to predict short-term cash flows.

This paper extends the existing literature in a number of ways. First, a simple accrual model assuming cash flows follow a random walk and current receivables and payables fully reverse in the subsequent period demonstrates that accruals can be used to enhance cash flow predictions. The paper further develops the estimation and specification of a accrual-based prediction model more sophisticated than the accrual reversal model. Specifically, it builds upon the model of Barth, Cram and Nelson (2001) to incorporate the role of ending inventory as an indication of management’s estimate of next period's sales. The paper explores firm and industry characteristics that are likely to affect the cross-sectional variability in the incremental predictive power of accrual models relative to models incorporating only cash flow information with respect to predictions of future cash flow.

Initial results indicate that the accrual-based prediction model based purely on the mechanical reversal of accruals produces significantly lower out-of-sample forecast errors than cash flow-based models and the more sophisticated accrual-based model. However, using a more powerful estimation procedure where the prior three years of data are pooled, the more sophisticated accrual-based model dominates all other models. The paper also finds that the incremental predictive power of both accrual-based models vary considerably with certain firm characteristics. In particular, the incremental predictive power of accrual models is decreasing with the volatility of sales, earnings, and the ratio of inventory to future sales and increasing with firm size.

Results show that the accrual model when estimated by pooling the prior three years' observations contains considerable information regarding future cash flow from future sales. Tests show that the accrual model contains significantly more information about cash flow from future sales than the cash flow-based model. Furthermore, tests are unable to detect any information in actual future sales regarding future cash flows incremental to the information contained in the accrual model for 13 of 17 industries.

A secondary contribution of this paper is the analysis of two alternative cash flow-based benchmark models used in the prior literature. Initial results find that a simple random walk model of cash flows produces lower out-of-sample forecast errors than a model regressing current cash flows on prior cash flows. Supplementary tests show that when the cash flow regression model is estimated by pooling the prior three years' observations, the cash flow regression model produces lower forecast errors than the random walk model. The predictive ability of the cash flow regression model relative to the random walk model increases as the volatility of the firms increase.

The paper proceeds as follows. Section 2 provides a review of prior literature. Section 3 develops the hypotheses regarding the ability of accruals to predict future cash flows and the relationship between firm characteristics and predictive ability. Section 4 discusses the sample selection. Section 5 provides initial empirical results. Section 6 performs ex-post analysis using alternative estimation procedures. Analyses are performed on the overall incremental predictive ability of the accrual model as well as the ability of the accrual model to forecast future cash flow associated with future sales. Section 7 offers conclusions.

2. Literature Review

Three research approaches have been used to assess empirically the usefulness of accruals relative to cash flows. One method relies on the value relevance of accruals through their association with concurrent stock prices. Lipe (1986) finds that various components of accrual earnings are associated with stock returns. Other researchers find an association between stock returns and accruals even after controlling for cash flows and/or aggregate earnings (Wilson 1986; Rayburn 1986; Bowen, Burgstahler, and Daley 1987; Dechow 1994).

The use of the value relevance approach for evaluating the usefulness of accruals has two shortcomings. First, as pointed out by Holthhausen and Watts (2001), the value relevance property has no obvious standard setting implications. Second, the measurement of value relevance studies relies on two assumptions: market efficiency and adequate control for risk. Yet, a number of "anomaly" studies have demonstrated that one or both of these assumptions do not hold. This study does not rely on either of these assumptions in assessing the usefulness of accruals in predicting future cash flows.

Another approach used by past research to assess the usefulness of accruals relies on the association between accruals, future cash flows, and future earnings. Greenberg, Johnson, and Ramesh (1986), Dechow, Kothari, and Watts (1998), Barth, Cram, and Nelson (2001), and Kim and Kross (2005) find an association between current period accruals and next period cash flows by regressing cash flows in period t+1 on cash flows and accruals in period t. An association is established by the significance of coefficients or an increase in explanatory power of the regression. Kim and Kross (2005) show that while the value relevance of earnings has decreased over time, the association between earnings and next period's cash flow has increased over time.[3] Dechow and Dichev (2002) uses a variation of the association approach by exploring the correlation between present accruals and cash flows in period t-1, period t, and period t+1.

Association studies find that for a given year, accruals are associated with future cash flows. The presence of an association, however, doesn't necessarily suggest incremental predictive ability of accruals with regard to future cash flows. The functional relationship may change over time.

[3] Kim, Lim, and Park (2005) conclude the association between earnings and one-year-ahead cash flows is not a substitute for the value relevance of accruals. They show that the increasing association between accruals and one-year-ahead cash flows found by Kim and Kross (2005) is not inconsistent with the decreasing value relevance of earnings.

A third approach to assess the usefulness of accruals relies on their incremental predictive ability (out-of-sample) with respect to future cash flows and earnings. Several studies look at the incremental predictive ability of aggregate earnings over cash flows alone. Bowen, Burgstahler, and Daley (1986) find no evidence earnings before extraordinary items is a better predictor of future operating cash flow than a random walk model of cash flows. In contrast, Dechow, Kothari, and Watts (1998) find that earnings before extraordinary items and discontinued operations do outperform a random walk model of operating cash flow. Although not the primary concern of their study, Kim and Kross (2005) find a prediction model incorporating earnings generated a lower Theil's U^2 than a prediction model incorporating cash flow only. However, their benchmark cash flow-based model is a regression of current cash flows on prior cash flows. As this study shows, a random walk model of cash flows produces smaller out-of-sample forecast errors than the regression model (when estimated over the preceding one year, as done in Kim and Kross) and should therefore serve as the benchmark for assessing accrual-based models' incremental predictive ability. Finally, employing time-series techniques, Finger (1994) did not find evidence that prior earnings contain incremental predictive ability beyond that of prior cash flows in predicting future cash flows. Overall, studies have not found consistent evidence that aggregate earnings are superior predictors of future cash flows than cash flows alone.

The Barth, Cram, and Nelson (2001) association study finds that disaggregated accruals have a higher association with future cash flows than earnings. This suggests that models using disaggregated accruals *may* have incremental predictive ability over cash flow-based models, even if models using total earnings do not. Lorek and Willinger (1996) find evidence of incremental predictive ability using a disaggregated accruals model. However, their study is based on a sample of 62 large successful firms and therefore cannot be generalized. Lev, Li, and Sougiannis (2005) employing a larger and more representative sample do not find evidence of incremental predictive power using disaggregated accrual models.

The inability of the Lev. et. al. (2005) study to detect the incremental predictive ability of disaggregated accrual models conflicts with the results of the value relevance and association studies. Further, this finding is puzzling, given the general belief (as expressed by the FASB) that accrual-based earnings are a better predictor of future performance than cash-based earnings. Lev et al. (2005) attribute their perplexing results to large estimation errors impounded in accruals, although they do not provide any direct evidence of such. This study investigates the incremental predictive ability of disaggregated accruals using a more refined prediction model than Lev, et. al.

3. Hypotheses and Research Design

3.1. The Model

Barth, Cram, and Nelson (BCN 2001) build on a model developed by Dechow, Kothari, and Watts (1998) to describe the effect of the current change in accruals on the expectation of future cash flow. BCN (2001) model sales as a random walk. In their model, management observes the current period sales shock and expects the shock to persist into the following period. Management strives to set inventory as a constant percentage of cost of goods sold, but the adjustment to purchases to achieve the desired level of inventory is partially made in the current period and partially in the following period. Therefore, the effect of the current period sales shock on purchases extends over the current and future periods. However, and in contrast to its effect on inventory, the effect of the current period sales shock on accounts receivable is limited to the current period. Therefore, in the original BCN model, accounts receivable contains information about future sales. As a result, accounts receivable predict both cash received from customers next period and the portion of next period inventory purchases that result from the current period sales shock.

The BCN model makes two questionable assumptions. The first assumption is that the change in sales has a zero expected value (i.e. no firm growth). The second assumption is that inventory changes are made only in response to observed sales shocks. The no growth assumption is unrealistic. Regarding the second assumption, it is likely that inventory changes reflect not only the current year's sales shock but also management's *anticipation* of future sales. That is, management sets the ending inventory level in anticipation of next period's sales. As a result, the ending inventory level can be used as a prediction of future sales. In this study, I extend the BCN model by allowing sales growth and tying ending inventory to management's expectation of future sales.

I make the following assumptions regarding earnings, sales, accounts receivable, and accounts payable, most of which are also made in the BCN model:

$$
\begin{aligned}
GP_t &= \pi S_t \\
OPEX_t &= \lambda S_t \\
EARN_t &= (\pi-\lambda)S_t \\
S_t &= S_{t-1} + G_t \\
AR_t &= \alpha S_t \\
AP_t &= \beta(PURCH_t+OPEX_t) \\
INV_t &= \gamma(1-\pi)(S_t+E_t(G_{t+1})) \qquad (1)
\end{aligned}
$$

where

π = Gross profit percentage,
α = Accounts receivable divided by sales,
β = Accounts payable divided by annual inventory purchases and operating expenses,
λ = Ratio of operating expenses to sales,
$EARN_t$ = Earnings for period t,
S_t = Sales for period t,
G_t = change in sales in period t,
AR_t = Accounts receivable at the end of period t,
AP_t = Accounts payable and accrued expenses at the end of period t,
$PURCH_t$ = Inventory purchases in period t,
$OPEX_t$ = Operating expenses in period t,
GP_t = Gross profit in period t,
INV_t= Inventory at the end of period t.
π, α, β and λ, γ are assumed to be constant over time.

The above assumptions differ from BCN in that I do *not* assume $E_t[G_{t+1}] = 0$ and I assume that managers strive to set ending inventory in period t to equal a constant percentage (denoted γ) of period t+1 expected COGS. The accrual-based cash flow prediction model below is developed by analyzing separately the accruals related to expected cash receipts and those related to expected cash payments.

Cash Receipts

Expected cash receipts are equal to expected sales less the expected change (denoted Δ) in AR:

$$E_t[CR_{t+1}] = E_t[S_{t+1}] - E_t[\Delta AR_{t+1}]$$
$$E_t[CR_{t+1}] = S_t + E_t[G_{t+1}] - E_t[\Delta AR_{t+1}]$$

Noting that $\Delta AR_t = \alpha G_t$:

$$E_t[CR_{t+1}] = S_t + E_t[G_{t+1}] - \alpha E_t[G_{t+1}]$$
$$E_t[CR_{t+1}] = S_t + (1-\alpha)E_t[G_{t+1}]$$

Since $CR_t = S_t - \Delta AR_t$:

$$E_t[CR_{t+1}] = CR_t + \Delta AR_t + (1-\alpha)E_t[G_{t+1}] \quad (2)$$

Cash Payments

Expected cash payments may be written as the expected cost of goods sold (COGS) plus expected operating expenses plus expected change in inventory less expected change in accounts payable, or in notational form:

$$E_t[CP_{t+1}] = [(1-\pi)+\lambda]E_t[S_{t+1}] + E_t[\Delta INV_{t+1}] - E_t[\Delta AP_{t+1}] \quad (3)$$

The first term, expected cost of goods sold plus operating expenses in period t+1, may be written as:

$$\begin{aligned} &[(1-\pi)+\lambda]E_t[S_{t+1}] = [(1-\pi)+\lambda](S_t + E_t[G_{t+1}]) \\ &= [(1-\pi)+\lambda]S_t + [(1-\pi)+\lambda]E_t[G_{t+1}] \end{aligned} \quad (4)$$

The first term, $[(1-\pi)+\lambda]S_t$, is COGS plus operating expenses in period t and can be written as:

$$[(1-\pi)+\lambda]S_t = CP_t + \Delta AP_t - \Delta INV_t$$

Substituting the above equation into equation 4 results in:

$$[(1-\pi)+\lambda]E_t[S_{t+1}] = CP_t + \Delta AP_t - \Delta INV_t + [(1-\pi)+\lambda]E_t[G_{t+1}] \quad (5)$$

The second term in equation 3, the expected change in inventory for period t+1, is proportional to the expected change in sales from period t+1 to period t+2:

$$\begin{aligned} &E_t[\Delta INV_{t+1}] = E_t[INV_{t+1}] - INV_t \\ &E_t[\Delta INV_{t+1}] = \gamma(1-\pi)[E_t[S_{t+2}] - E_t[S_{t+1}]] \end{aligned}$$

Since $E_t[S_{t+2}] - E_t[S_{t+1}] = E_t[G_{t+2}]$:

$$E_t[\Delta INV_{t+1}] = \gamma(1-\pi)E_t[G_{t+2}] \quad (6)$$

The final component of expected cash payments (the final term in equation 3) is the expected change in accounts payable for period t+1:

$$E_t[\Delta AP_{t+1}] = \beta(E_t[\Delta PURCH_{t+1} + \Delta OPEX_{t+1}]) \tag{7}$$

Noting that purchases equal COGS plus the change in inventory:

$$PURCH_t = (1-\pi)S_t + \Delta INV_t$$
$$E_t[PURCH_{t+1}] = (1-\pi)(S_t + E_t[G_{t+1}]) + E_t[\Delta INV_{t+1}]$$

The expected change in purchases may be written as $E_t[PURCH_{t+1}]$ - $PURCH_t$:

$$E_t[\Delta PURCH_{t+1}] = (1-\pi)E_t[G_{t+1}] + E_t[\Delta INV_{t+1}] - \Delta INV_t$$

Recalling that $E_t[\Delta INV_{t+1}]=\gamma(1-\pi)E_t[G_{t+2}]$:

$$E_t[\Delta PURCH_{t+1}] = (1-\pi)E_t[G_{t+1}] + \gamma(1-\pi)E_t[G_{t+2}] - \Delta INV_t \tag{8}$$

The expected change in operating expenses can be derived as:

$$OPEX_t = \lambda S_t$$
$$E_t[OPEX_t] = \lambda(S_t + E_t[G_{t+1}])$$
$$E_t[\Delta OPEX_t] = \lambda E_t[G_{t+1}] \tag{9}$$

By substituting equations 8 and 9 into equation 7, expected change in accounts payable can be written as:

$$E_t[\Delta AP_{t+1}] = \beta[[(1-\pi)+\lambda]E_t[G_{t+1}] + \gamma(1-\pi)E_t[G_{t+2}] - \Delta INV_t] \tag{10}$$

Finally, total expected cash payments is calculated as equation 5 plus equation 6

less equation 10:

$$\begin{aligned}E_t[CP_{t+1}] &= \{CP_t + \Delta AP_t - \Delta INV_t + [(1-\pi)+\lambda]E_t[G_{t+1}]\}\\ &+ \{\gamma(1-\pi)E_t[G_{t+2}]\}\\ &- \beta\{[(1-\pi)+\lambda]E_t[G_{t+1}] + \gamma(1-\pi)E_t[G_{t+2}] - \Delta INV_t\}\end{aligned}$$

$$\begin{aligned}E_t[CP_{t+1}] &= CP_t + \Delta AP_t - (1-\beta)\Delta INV_t + (1-\beta)[(1-\pi)+\lambda]E_t[G_{t+1}]\\ &+ (1-\beta)\gamma(1-\pi)E_t[G_{t+2}]\end{aligned} \tag{11}$$

Expected Net Cash Flows

Expected net cash flows is the difference between expected cash receipts and expected cash payments (equation 2 minus equation 11):

$$E_t[CF_{t+1}] = E_t[CR_{t+1}] - E_t[CP_{t+1}]$$
$$E_t[CF_{t+1}] = CR_t + \Delta AR_t + (1-\alpha)E_t[G_{t+1}]$$
$$-\{CP_t + \Delta AP_t - (1-\beta)\Delta INV_t + (1-\beta)[(1-\pi)+\lambda]E_t[G_{t+1}] + (1-\beta)\gamma(1-\pi)E_t[G_{t+2}]\}$$

Rearranging and simplifying results in:

$$\begin{aligned} E_t[CF_{t+1}] &= CF_t + \Delta AR_t - \Delta AP_t + (1-\beta)\Delta INV_t \\ &+ [(1-\alpha) - (1-\beta)[(1-\pi)+\lambda]]E_t[G_{t+1}] - (1-\beta)\gamma(1-\pi)E_t[G_{t+2}] \end{aligned} \tag{12}$$

Since management incorporates $E_t[G_{t+1}]$ in INV_t, $E_t[G_{t+1}]$ can be stated in terms of period t ending inventory and sales. Recalling from equation 1 that $INV_t=\gamma(1-\pi)E[S_{t+1}]$, the expected change in sales can be derived:

$$\begin{aligned} INV_t &= \gamma(1-\pi)(S_t + E_t[G_{t+1}]) \\ E_t[G_{t+1}] &= \frac{INV_t}{\gamma(1-\pi)} - S_t \end{aligned} \tag{13}$$

Substituting equation 13 into equation 12 results in:

$$E_t[CF_{t+1}] = CF_t + \Delta AR_t - \Delta AP_t + (1-\beta)\Delta INV_t$$
$$+ [(1-\alpha) - (1-\beta)((1-\pi)+\lambda)]\left[\frac{INV_t}{\gamma(1-\pi)} - S_t\right] - (1-\beta)\gamma(1-\pi)E_t[G_{t+2}]$$

$$\begin{aligned} E_t[CF_{t+1}] &= CF_t + \Delta AR_t - \Delta AP_t + (1-\beta)\Delta INV_t + \left[\frac{(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]}{\gamma(1-\pi)}\right]INV_t \\ &- [(1-\alpha)-(1-\beta)((1-\pi)+\lambda)]S_t - (1-\beta)\gamma(1-\pi)E_t[G_{t+2}] \end{aligned} \tag{14}$$

Equation 14 delineates the links between current period accruals and next period's cash flows. First, $INV_t/\gamma(1-\pi)$ provides a prediction of sales in t+1, $E_t(S_{t+1})$. Second, the coefficient $[(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]]$ maps the expected change in sales,

$E_t(S_{t+1}) - S_t$, into expected future cash flow. Finally, the coefficient $(1-\beta)\gamma(1-\pi)$ adjusts expected future cash flow for the change in t+1 inventory purchases that result from the expected change in sales from t+1 to t+2, $E_t(G_{t+2})$. The prediction power of equation 14 depends upon all three of these factors.

Equation 14 is leads to the main hypothesis of the paper, which is:

H1: Cash flow forecast models incorporating accrual information outperform models incorporating only cash flow information.

3.2. Research Design

3.2.1. Cash flow-based prediction models

I use two cash flow-based prediction models to serve as benchmarks for assessing the incremental predictive ability of accrual models. The first model assumes cash flows behave as a random walk. A random walk model serves as the benchmark model in Bowen, Burgstahler, and Daley (1986) and Dechow, Kothari, and Watts (1998).

Random Walk Cash Flow Model (Model CFRW):

$$E(CFO_{i,t+1}) = CFO_{i,t} \qquad (15)$$

where

$CFO_{i,t}$ = Cash flow from operations of firm i in period t.

The second cash flow-based model predicts next period's cash flows as a linear function of current cash flows. The following regression is estimated from a cross-section of firms within industry and year:[4]

[4] All least squares regressions in this study are estimated by scaling all variables (including the intercept) by average total assets. This is commonly referred to as a weighted least squares (WLS) regression

Cash Flow Regression Model (Model CFREG):

$$E(CFO_{i,t+1}) = \theta_0 + \theta_1 CFO_{i,t} \tag{16}$$

Kim and Kross (2005) and Lev et al. (2005) use this benchmark model. Note that unlike the random walk model (CFRW), which constrains θ_0 to zero and θ_1 to one, the cash flow regression model (CFREG) allows these coefficients to vary. The appropriate cash flow benchmark model to assess the incremental predictive ability of accrual models is the more accurate of models 1 and 2.

3.2.2. Accrual-based prediction models

The first accrual-based prediction model assumes cash flows behave as a random walk and that working capital accruals are fully collected or paid in the following period. Specifically, the model is:

Accrual Reversal Model (Model ACCREV)

$$E(CFO_{i,t+1}) = CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t} \tag{17}$$

For instance, assume accounts receivable of \$100 in period t-1 and \$150 in period t. This model assumes that the \$100 of accounts receivable in period t-1 is collected in period t and the \$150 of accounts receivable in period t is collected in period t+1. All else equal, cash collected in period t+1 should be \$50 higher (equal to the change in accounts receivable) than cash collected in period t.

The second and third accrual-based models are based on the analytical model summarized in equation 14. I separate accounts payable included in the analytical model (equation 14) into accounts payable, accrued expenses (AccExp), and accrued

---

(Studenmund 1997, page 385. Greene 2000, page 512.) This approach applies less weight to large observations thus preventing large observations from dominating the coefficients.

income taxes (AccIT) for testing purposes. With the addition of AccExp and AccIT, the accrual model from section 3 becomes:

Accrual Parameters Model (Model ACCPAR):

$$
\begin{aligned}
E(CFO_{i,t+1}) = {} & CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t} + (1-\beta)\Delta INV_{i,t} \\
& + \left[\frac{(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]}{\gamma(1-\pi)}\right] INV_{i,t} - [(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]]S_{i,t} \qquad (18) \\
& - (1-\beta)\gamma(1-\pi)E\Delta Sales2_{i,t}
\end{aligned}
$$

where

$CFO_{i,t}$ =	Cash flow from operations for firm i in period t,
$\Delta AR_{i,t-1}$ =	Change in accounts receivable for firm i in period t,
$\Delta INV_{i,t}$ =	Change in inventory for firm i in period t,[5]
$\Delta AP_{i,t}$ =	Change in accounts payable for firm i in period t,
$\Delta AccExp_{i,t}$ =	Change in accrued expenses for firm i in period t,
$\Delta AccIT_{i,t}$ =	Change in accrued income taxes for firm i in period t,
$INV_{i,t}$ =	Level of inventory for firm i at the end of period t,
$S_{i,t}$ =	Level of sales for firm i in period t,
$E\Delta Sales2_{i,t}$ =	The expectation at the end of period t of the change in sales from period t+1 to period t+2.

The Accrual Parameters Model (ACCPAR) given in equation 18 requires a proxy for the expectation of the change in sales from period t+1 to t+2 (EΔSales2). While analysts' forecasts of sales would likely be a good proxy, these two-year-ahead sales forecasts are not available. An alternative proxy assumes management expects firm growth in year t+1 and t+2 to continue at the rate of year t growth (g). The growth rate is calculated $g=S_t/S_{t-1}$. The expected change in sales from period t+1 to period t+2 can then be calculated as (g^2-g) times S_t. The Pearson correlation between g and analysts' forecasts of one-year-ahead growth in sales is 0.43 and significant at less than

[5] The change in inventory is likely a worse measure of expected future growth for LIFO firms. Therefore, I restate the inventory values of LIFO firms to conform with FIFO using the LIFO reserve reported on Compustat.

a 1% significance level. Estimation of the model requires estimates of the parameters α, β, γ, π, and λ. These parameters are derived as the average parameter for each firm over the current and prior two years.

Accruals Regression Model (Model ACCREG):

$$E\left(CFO_{i,t+1}\right) = \theta_0 + \theta_1 CFO_{i,t} + \theta_2 \Delta AR_{i,t} + \theta_3 \Delta AP_{i,t} + \theta_4 \Delta AccExp_{i,t} + \theta_5 \Delta AccIT_{i,t} + \theta_6 \Delta INV_{i,t} + \theta_7 INV_{i,t} + \theta_8 S_{i,t} + \theta_9 E\Delta Sales2_{i,t} \quad (19)$$

The Accrual Regression Model's (ACCREG) variables are identical to those of the Accrual Parameters Model (ACCPAR). However, in contrast to ACCPAR, ACCREG estimates a cross-sectional coefficient (by industry and year) for each variable using a weighted least square regression instead of using firm specific individual parameters. A comparison of the forecast errors from ACCPAR and ACCREG will indicate how well the use of firm-specific estimates improves the predictive power of accruals and how well the model parameters capture the relationship between current accruals and future cash flows.

The predictive ability of the models considered is gauged by their absolute forecast errors. In assessing the incremental predictive ability[6] of each accrual-based model, its prediction errors are compared to the prediction errors produced by the more accurate cash flow-based model.

[6] Incremental predictive ability in this study refers to the difference in predictive ability of any two models being compared. Other literature often refers to incremental predictive ability as the increase in predictive ability of an existing model when a variable of interest is added.

3.3. Firm characteristics affecting the predictive ability of accrual models

This section discusses a number of firm characteristics hypothesized to affect the incremental predictive ability of accrual-based models: stability of the ratio of inventory to future sales, volatility of sales and earnings, and firm size. [7]

3.3.1. Stability of the ratio $INV_t/SALES_{t+1}$

As is evident from the accrual models, next period sales affects next period's cash flows. The accrual models use ending inventory to predict future sales. The power of inventory to predict future sales depends on the validity of the model assumption that inventory at time t equals a percentage, γ, of period t+1 cost of goods sold (i.e. $INV_t=\gamma(1-\pi)Sales_{t+1}$.) The more stable the ratio of inventory to sales, the more reliable the inventory-based sales forecast. This leads to:

H2: The incremental predictive ability of the accrual model is decreasing in the volatility of the ratio of ending inventory to future sales.

The firm-specific volatility of the inventory ratio (IRVOL) is computed as the standard deviation of $INV_t/Sales_{t+1}$ over all years in the sample period.[8] If the ability of inventory to predict future sales contributes to the incremental predictive ability of accrual models, IRVOL should be negatively correlated with the incremental predictive ability of accrual models.

3.3.2. Volatility of Sales and Earnings

The volatility of sales and volatility of earnings reflect the volatility of a firm's operating environment. I expect the volatility of cash flow to be increasing with the

---

[7] Dechow and Dichev (2002) find that the volatility of sales, the volatility of earnings, and firm size are all correlated with the error with which past, present, and future cash flows map into accruals. This study builds upon Dechow and Dichev by determining whether these characteristics affect the out-of-sample predictive ability of accruals in the same manner as documented in their association tests.

[8] I require a firm to have at least five annual observations to be included in this portion of the analysis.

volatility of sales and the volatility of earnings. This increase in the volatility of cash flow should result in higher forecast errors under both cash flow-based and accrual-based models. In addition, the volatility of sales and earnings will likely have an impact on the volatility of the accrual model parameters and sales estimation error impounded in inventory. However, whether the volatility of sales and earnings will have an effect on the incremental predictive power of the accrual model over the cash flow model and the direction of that effect are empirical questions. Hence, hypothesis three is two-sided:

H3: The incremental predictive ability of the accrual model over a cash flow-only model will vary in the volatility of sales and the volatility of earnings.

3.3.3. Firm size

Larger firms are likely to have more stable accrual model parameters due to a larger and more diversified client and vendor base. For small firms, the parameters of the model may be significantly affected by a relatively small number of contracts or customers. For instance, if a large customer of a small firm delays payment on an account receivable, the ratio AR_t/S_t could be significantly affected creating a larger volatility in AR_t/S_t. In contrast, the ratio of AR_t/S_t for a large firm is less likely to be affected by the payment pattern of any one customer.

Firm size is likely to be negatively correlated with the volatility of cash flows. Therefore, I expect the predictive ability of both the accrual-based and cash flow-based model to be increasing with firm size. However, due to the effect of size on the stability of the accrual model parameters, I expect the effect of size on the accrual-based models to be larger than that on the cash flow-based models. Hence:

H4: The incremental predictive ability of the accrual model over a cash flow-only model is increasing in firm size.

Hypotheses 2 through 4 are tested by examining the Spearman correlation between firm characteristics and the incremental predictive ability of the Accrual Reversal Model (ACCREV), the Accrual Parameters Model (ACCPAR), and the Accrual Regression Model (ACCREG) over the Cash Flow Random Walk Model (CFRW) and the Cash Flow Regression model (CFREG). To further test the effect of firm characteristics on the incremental predictive ability of the accrual models, firms are ranked based on the firm characteristics and partitioned into portfolios. The models are then estimated within each quartile of the characteristic's distribution and the forecast errors of each quartile is examined.

4. Sample Selection

The sample consists of firm years from 1989 through 2004 for firms in the manufacturing (SIC 1500 through 3999), wholesale (SIC 5000 through 5199), and retail (SIC 5200 through 5799 and 5900 through 5999) industries. These industries were chosen for their inventory intensity. Since the accrual model derives a prediction of future sales from ending inventory, it is not descriptive of the accrual process for industries in which inventory is not a major accrual. All data are collected from Compustat. To be included in the final sample, firm-years are required to have cash flows from operations, positive total assets, positive sales, positive cost of goods sold, change in accounts receivable, change in accounts payable, change in accrued expense, and change in inventory[9]. In order to estimate the Accrual Parameters Model (ACCPAR), firm-years are included only if information for the current and prior two years is available for accounts receivable, accrued expense, accounts payable, and inventory. Finally, cash flows from operations for the following year must be available. Because SFAS 95 which mandates the disclosure of the Statement of Cash Flows was effective for firm years ending July 1988 or later, the sample begins with 1989. The last estimation of the models is made for 2003, the last year for which the subsequent year's data is available. The above selection process results in a sample of 28,992 firm years.

Firms are grouped into industries based on three-digit SIC codes. For three-digit SIC codes containing fewer than twenty firms in any of the fifteen sample years, I use instead two-digit SIC codes. Each two-digit grouping must have at least twenty firms in each of the fifteen sample years. Firms belonging to two-digit industries that have fewer than 19 industry peers in any one of the sample years are discarded. This elimination results in a final sample of 25,487 firm-years belonging to 3,736 unique firms affiliated with 31 industries (14 three-digit industries and 17 two-digit industries).

5. Results

5.1. Descriptive statistics

Table 2, panel A presents the distribution of financial statement variables for the sample. The mean (median) average total assets of firm-years included in the main

[9] The change in accruals is taken from the statement of cash flow when available. If not available, the change is calculated as the difference between the current period accrual and the prior period accrual. With the exception of ΔAccIT, if the statement of cash flow information is not available and either the current or prior period accrual is missing, the observation is discarded. If information is not available for ΔAccIT, ΔAccIT for that observation is set to zero.

sample are \$1.9 billion (\$170 million). The mean (median) sales of sample firm-years are \$2.1 billion (\$216 million).

Table 2, panel C presents the distribution of the firm-specific model parameters and the firm characteristics. The mean ratio of end-of-year accounts receivable to sales (α) is 17%. The mean ratio of end-of-year accounts payable to payments to vendors (β) is 16%. Ending inventory represents, on average, 30% of next period cost of goods sold (γ). The mean gross profit percentage (π) is 36% while operating expenses average 31% of sales (λ).

Table 2, panel D presents the correlations between the accrual model's parameters and firm characteristics. Two correlations are particularly high. The Pearson correlation between the ratio of operating expense to sales (λ) and gross profit percentage (π) is .52. The high correlation likely reflects the substitution between discretionary costs, such as R&D and advertising, and gross profit margins. High levels of these discretionary costs are typically accompanied by high gross profit margin.

The second high correlation from Table 2, Panel B is the .53 correlation between IRVOL and γ. Recall that the variables are defined as:

$$IRVOL = std\left(\frac{INV_t}{S_{t+1}}\right)$$

$$\gamma = \frac{INV_t}{COGS_{t+1}}$$

where std is the standard deviation operator, INV is inventory, S is sales, and COGS is cost of goods sold. The high correlation may reflect a magnitude phenomenon. The higher the level of the ratio of inventory to future cost of goods sold (γ), the higher its variability (as well as the variability of the related ratio of inventory to future sales).

5.2. Cash flow predictions.

As explained earlier, the coefficients in the Cash Flow Regression Model (CFREG) and the Accrual Regression Model (ACCREG) are estimated by regressing year t cash flows on year t-1 observations of the independent variables. The coefficients in the Accrual Parameters Model (ACCPAR) are estimated by applying the individual parameters averaged over years t, t-1, and t-2. These estimates are applied to year t observations of the independent variables to arrive at an estimate of year t+1 cash flow. Table 3, panel B presents the coefficients from estimating the cash flow-based CFREG and the accrual-based models ACCPAR and ACCREG. The Cash Flow Random Walk Model (CFRW) and Accrual Reversal Model (ACCREV) do not require estimation as the coefficients on cash flow and accruals is restricted to equal 1. With the exception of the coefficients on INV_{t-1} and $Sales_{t-1}$ in ACCREG, all coefficients are significant and in the direction predicted by the model. The coefficients reported are the average coefficients across years and industries. While the average coefficients on INV_{t-1} and $Sales_{t-1}$ are insignificant, they may be significant within certain industries. However, the focus of this paper is on out-of-sample predictions versus the analysis of regression coefficients.

Table 3, panel C presents the out-of-sample absolute forecast errors generated by each model. The Accrual Reversal Model (ACCREV) reports the lowest median absolute forecast error of 50.8% of cash flow from operations. The Cash Flow Random Walk Model (CFRW) reports a lower absolute forecast error than the Cash Flow

Regression Model (CFREG) at 52.8% of cash flow from operations. The Accrual Regression Model (ACCREG) does not perform as well as CFREG with a median absolute forecast error of 55.9% of cash flow from operations. However, supplementary tests discussed later show that ACCREG does produce lower absolute forecast errors than CFREG and CFRW when estimated while pooling the prior three years of observations.

Table 4 investigates whether the absolute forecast errors reported in table 3, panel C are significantly different from one another. An ANOVA is used to test for differences in forecast ability across models. Since an ANOVA assumes that the variance of forecast errors does not vary across firms (which is not likely true in this study), an ANOVA on ranks is performed.[10] Models are ranked from one to five within each firm-year with one being assigned to the model generating the lowest absolute forecast error and five being assigned to the model with the highest absolute forecast error. An ANOVA is performed on these ranks using a complete block design where each block consists of exactly one firm-year. Each firm-year has five observations consisting of the rank of each of the five models. Table 4, panel A reports that the null hypothesis of no difference between forecast methods is easily rejected under both an F-Test and the Friedman χ^2.

Table 4, panel B presents the mean rank of forecast errors generated by each model. A Bonferonni pairwise comparison shows that the mean rank of errors from

[10] See Neter et. al., page 1094 for a discussion of this methodology. There is likely serial correlation between the rankings of methods across years for the same firm. One possible solution is given in Diebold and Mariano (1995) where paired t-tests are performed while adjusting the standard errors for serial correlation. Future work in this area may address possible effects of serial correlation on any conclusions drawn.

each prediction model is significantly different.[11] The order of the ranking agrees with the median absolute forecast errors presented in Table 3, panel C. The models ranked from lowest absolute forecast errors to highest absolute forecast errors are: Accrual Reversal Model (ACCREV), Cash Flow Random Walk Model (CFRW), Accrual Regression Model (ACCREG), Cash Flow Regression Model (CFREG), and Accrual Parameters Model (ACCPAR). Therefore, ACCREV has incremental predictive ability beyond that of both CFRW and CFREG. There is no evidence that either ACCREG or ACCPAR contains incremental predictive ability beyond that of CFRW. Note that had the incremental predictive ability of ACCREG been tested with reference to only the CFREG benchmark (as done in Kim and Kross, 2005) the conclusion would have been that ACCREG has incremental predictive ability. This highlights the importance of using the appropriate cash flow benchmark model when assessing incremental predictive ability.

As shown in table 4, panel B, ACCREV produces errors with a significantly lower mean rank than either ACCPAR or ACCREG. This may be interpreted as the mechanical reversal of accruals providing information about future cash flows, but accruals not containing additional information about future economic activity (i.e. future sales). However, supplementary analysis discussed later reports that ACCREG produces forecast errors with a significantly lower mean rank than ACCREV when estimated while pooling the prior three years of observations.

[11] See Neter et al. page 1096 for the necessary modifications to the Bonferonni test when working with a ranked ANOVA.

5.3. Effect of firm characteristics on incremental predictive ability

Table 5, Panel A provides the correlation between firm characteristics and the absolute forecast errors of all five models. The absolute forecast errors of all models are increasing in the volatility of the inventory ratio (IRVOL), earnings (EARNVOL), and sales (SALESVOL) and decreasing in average total assets (AVGTA). Table 5, panel B provides the correlations between firm characteristics and the *incremental* predictive abilities of the models. The first row in panel B finds that the predictive ability of the Cash Flow Regression Model (CFREG) compared to the Cash Flow Random Walk Model (CFRW) is increasing in all three measures of volatility. CFRW forecasts next period cash flows as current period cash flows (i.e. CFRW assumes cash flows are 100% persistent), whereas CFREG estimates the persistence of current cash flows as the persistence of prior cash flows. Therefore, CFREG performs better than CFRW as volatility increases and cash flows become less persistent. Since CFREG is affected less by increased volatility than CFRW, it is the proper benchmark for assessing the affect of volatility on the incremental predictive ability of the accrual models.

The fifth row of table 5, panel B shows that the incremental predictive ability of the Accrual Reversal Model (ACCREV) over the Cash Flow Regression Model (CFREG) is decreasing in all three measures of volatility. As with the Cash Flow Random Walk Model (CFRW), ACCREV assumes cash flows (aside from reversals) behave as a random walk. While the inclusion of the reversal of receivables and payables may help to account for some cash flow volatility, ACCREV does not account for volatility as well as CFREG (which estimates the persistence of current cash flows as the persistence of prior cash flows).

Table 5, panel B, rows 6 and 7 provide the results of testing hypotheses 2, 3, and 4. Consistent with all three hypotheses, the incremental predictive ability of the Accrual Regression Model (ACCREG) over the Cash Flow Regression Model (CFREG) is decreasing with the volatility of the inventory ratio (IRVOL), earnings (EARNVOL), and sales (SALESVOL) and increasing with average total assets (AVGTA). However, the incremental predictive ability of the Accrual Parameters Model (ACCPAR) over CFREG is only decreasing in EARNVOL. While ACCPAR depends heavily on the stability of the individual parameters, it has weak predictive ability as shown table 3, panel C. The large amount of noise contained in ACCPAR predictions makes it difficult to detect the hypothesized effects of firm characteristics.

Table 6 further examines the effect of firm characteristics on incremental predictive ability by separating firms into quartiles based on each of the four firm characteristics investigated. Once separated into quartiles, the Cash Flow Regression Model (CFREG) and Accrual Regression Model (ACCREG) are estimated across all firms in that quartile (versus within industries). This is necessary since there are insufficient observations within each industry and quartile to adequately estimate the parameters.

The most striking result in all four panels of table 6 is that the Accrual Regression Model (ACCREG) has positive incremental predictive ability over both the Cash Flow Random Walk Model (CFRW) and the Cash Flow Regression Model (CFREG) in all four quartiles of each firm characteristic. This is in sharp contrast to the inability to detect the positive incremental predictive ability of ACCREG in table 3, panel D. This suggests a lack of power in the estimation procedure employed in table 3 to arrive at the coefficients of ACCREG. Assuming the forecasts are unbiased such that the expected forecast error is zero, the absolute forecast error of ACCREG is increasing in the variance of the coefficients applied. Apparently, estimating the coefficients within quartiles (versus 31 industries) in table 7 is arriving at less noisy estimates of the coefficients than in table 3. Supplementary analysis is performed later in the paper increasing the power of the estimation by reducing the number of industries from 31 to 17 and increasing the number of observations per industry by pooling observations from year t-2 through year t.

The first row in panels A through D of table 7 show that the superior cash flow benchmark model varies with all four firm characteristics. The Cash Flow Random Walk Model (CFRW) produces lower absolute forecast errors than the Cash Flow Regression Model (CFREG) for firms in the lowest quartile of IRVOL, EARNVOL, and SALESVOL while CFREG produces the lower absolute forecast errors in the highest quartile of these characteristics. This is consistent with the positive correlation found in table 5, panel B between the incremental predictive ability of CFREG over CFRW and all three volatility measures. In addition, the superiority of CFREG over CFRW is smaller in the fourth quartile of AVGTA than in the first quartile. This is an important finding in that it implies the appropriate benchmark to measure incremental predictive ability of accrual models for firms with high volatility or low total assets is CFREG while the appropriate benchmark model is CFRW for firms with low volatility or high total assets.

The Accrual Reversal Model (ACCREV) is not superior to the Cash Flow Regression Model (CFREG) any quartile of AVGTA (table 6, panel D). This is in contrast to the superiority of ACCREV over CFREG in each quartile of the other three firm characteristics. Apparently, CFREG is more powerful when estimated within quartiles of AVGTA versus quartiles of volatility. This is possibly due to less cross-sectional variation in the persistence of cash flows within quartiles of AVGTA than within quartiles of volatility.

Consistent with the findings in table 5, panel B, the incremental predictive ability of the Accrual Reversal Model (ACCREV) over the Cash Flow Regression Model (CFREG) (shown in the fifth row) is significantly less in the fourth quartile of each volatility measure than in the first quartile. In addition, no evidence is found that ACCREV produces lower absolute forecast errors than CFREG in the highest quartile of each volatility measure. Therefore, while ACCREV does contain incremental predictive ability on average, there is no evidence the ACCREV contains incremental predictive ability for highly volatile firms.

Hypothesis 2 predicts that the volatility of $inventory_{t-1}/sales_t$ (IRVOL) will affect the ability of inventory to predict future sales, and thus affect the incremental predictive ability of both the Accrual Parameters Model (ACCPAR) and the Accrual Regression Model (ACCREG). Consistent with the findings in the prior table, table 6, panel A fails to find evidence of a decrease in the incremental predictive ability of ACCPAR over CFREG from the first to fourth quartile of IRVOL. Consistent with hypothesis 2, the mean incremental predictive ability of ACCREG over CFREG is lower in the fourth quartile of IRVOL than in the first. However, the decrease is not monotonic nor does the median incremental forecast ability differ between the first and fourth quartiles.

Hypothesis 3 predicts that the incremental predictive ability of the Accrual Parameters Model (ACCPAR) and the Accrual Regression Model (ACCREG) is decreasing in EARNVOL and SALESVOL. Table 7, panels B and C find that the incremental predictive ability of ACCPAR with respect to the Cash Flow Regression Model (CFREG) is higher (less negative) in the first quartile of EARNVOL and SALESVOL than in the fourth quartile. However, while the incremental predictive ability of ACCPAR may vary with EARNVOL and SALESVOL, it is still negative in all quartiles of both volatility measures. Contrary to the findings in table 5, table 6 panels B and C do not find evidence of a decrease in the incremental predictive ability of ACCREG over CFREG across the first and fourth quartile of either EARNVOL or SALESVOL. However, the incremental predictive ability of ACCREG over CFREG is positive in all quartiles of both EARNVOL and SALESVOL.

Hypothesis 4 predicts that the incremental predictive ability of the Accrual Parameters Model (ACCPAR) and the Accrual Regression Model (ACCREG) is increasing in size. Consistent with the hypothesis, table 7, panel D finds that the incremental predictive ability of ACCPAR over CFREG in the fourth quartile is significantly higher (less negative) than in the first quartile. However, the incremental predictive ability of ACCPAR over CFREG is still negative in each of the size quartiles. No evidence is found of a size effect on the incremental predictive ability of ACCREG over CFREG.

5.4. Industry Analysis

Table 7, panel A presents the absolute forecast errors of the prediction models for each of the 31 industries included in the study. Table 7, panel B presents the results of the ranked ANOVA testing the significance of the differences between mean ranks of prediction models by industry. Table 7, panel B demonstrates that the best performing cash flow-based model may vary across industries. The Cash Flow Random Walk Model (CFRW) produces significantly lower errors than the Cash Flow Regression Model (CFREG) for 10 of the 31 industries.

Consistent with the overall results reported in Table 3, Table 7, panel B reveals that the Accrual Reversal Model (ACCREV) produces absolute forecast errors with a smaller mean rank than the Cash Flow Random Walk Model (CFRW) for most industries. Twenty-five of 31 industries report ACCREV produces smaller errors than CFRW. However, only three of these 23 industries report the difference in mean ranks is significant at the 5% level. The large number of insignificant differences at the industry level is at least partly due to the lower power associated with fewer observations when compared to the tests across all industries.

5.5. Summary of initial results

The primary finding from the initial results is that cash flow predictions based on a random walk in cash flow adjusted for the expected complete reversal of current payables and receivables (ACCREV) produces lower out-of-sample forecast errors, on average, than either a random walk model of cash flows (CFRW) or a cash flow regression model (CFREG). Therefore, accruals do contain incremental predictive ability when applied to the ACCREV model. There are two instances when ACCREV does not perform significantly better than CFREG: when earnings and sales are volatile and when CFREG is calculated within quartile of AVGTA. Finally, the results indicate that while the incremental predictive ability of the accrual model based on the individually estimated model parameters (ACCPAR) with respect to CFREG is decreasing with the volatility of earnings and sales and increasing with average total assets, positive incremental predictive ability of ACCPAR is not detected in any quartile based on volatility and size.

The initial analysis also reveals that the procedure used to estimate ACCREG suffers from a lack of power due to too few observations per industry-year. While the analysis calculated within industries and years found no evidence of positive incremental predictive ability (table 3), the analysis by quartiles of firm characteristics (table 7) found positive incremental predictive ability within each quartile of each firm characteristic. The next section discusses supplementary analysis using a more powerful procedure to estimate the parameters in ACCREG.

6. Supplementary Analyses using Alternative Estimation Procedures

6.1. Description of Alternative Estimation Procedure

The analysis in the previous section revealed that incremental predictive ability of ACCREG is detected when the model is estimated within quartiles of firm characteristics, but not when estimated within industries. A more powerful industry specific estimation procedure is needed to analyze the incremental predictive ability of ACCREG across different industries. The number of observations over which the coefficients of ACCREG are estimated is increased two ways. First, the number of separate industries is reduced from 31 to 17. Firms are grouped such that no firm-years are omitted due to insufficient observations. This increases the number of firm-year observations from 25,487 to 28,992. Table 8 lists and describes the alternative industry groupings. Second, firm-years t-2 through t are pooled to calculate the coefficient to apply to year t in forecasting year t+1 cash flows. This implicitly assumes the coefficients in ACCREG are constant over three years. The CFREG cash flow-based benchmark model is also estimated under the alternative procedures.

6.2 Cash flow predictions using alternative estimation procedures

Table 9 presents the absolute forecast errors for the CFRW, CFREG, ACCREV, and ACCREG models. ACCREG has a median absolute cash flow forecast error of 51.2% of cash flow from operations, whereas the best performing cash flow-based model (CFRW) has a median absolute cash flow forecast error of 54.7% of cash flow from operations. Table 10, panel B presents the ranked ANOVA results showing that the difference in forecasting ability between each model is significant. The models are ranked from lowest absolute forecast error to highest absolute forecast error in the following order: ACCREG, ACCREV, CFRW, and CFREG. In contrast to the original results, both accrual-based models contain incremental predictive ability relative to both cash flow-based models. ACCREG also produces lower forecast errors than ACCREV indicating that accruals contain more information about future cash flows than their simple mechanical reversal.

Table 11, panel B, presents the correlations between the differences in absolute forecast errors between models and the industry characteristics. As in the main analysis, the predictive ability of CFREG compared to CFRW increases with all three measures of volatility. As discussed in section 5.3, CFREG partially accounts for cash flow volatility by forecasting future cash flows as the persistent portion of current cash flows. Since CFREG better controls for volatility, it is the appropriate cash flow-benchmark to assess the effect of volatility on the incremental predictive ability of ACCREG. As predicted in hypotheses 2, 3, and 4, (and consistent with the results reported in the main analysis in table 5, panel B) the incremental predictive ability of ACCREG over CFREG is decreasing in the volatility of the inventory ratio (IRVOL), earnings (EARNVOL), and sales (SALESVOL) and increasing in average total assets (AVGTA).

Table 11, panel B also reports that the superiority of ACCREG over ACCREV is increasing in all three volatility measures and decreasing in AVGTA. Dechow and Dichev (2002) show that as the volatility of earnings and sales increases and firm size decreases, the mapping of accruals into cash flows decreases. ACCREV assumes that payables and receivables map perfectly into next year's cash flows. ACCREG estimates the effect of current accruals on next period's cash flows through a cross-sectional regression of current period cash flows on prior period accruals. As the volatility of sales and earnings increase and firm size decreases (and thus the mapping of accruals into future cash flow decreases) the assumption of perfect mapping in ACCREV becomes problematic and the estimation in ACCREG becomes more important.

6.3. Cash flow predictions by industry using alternative estimation procedures

Table 12, panel b presents the results of the Bonferonni pairwise comparisons of the ranked forecast error of each model by industry using the alternative estimation procedures. Consistent with the overall results in table 9, ACCREG has significant incremental predictive ability over both CFRW and CFREG for 10 of the 17 industries.

Table 12, panel b reports that the Food and Tobacco industry is the only industry in which forecast errors from CFRW or CFREG have a significantly lower mean rank than forecast errors of ACCREG. Tobacco firms are driving this weakness in ACCREG compared to CFRW. When tobacco firms are removed from the food and tobacco industry and ACCREG is re-estimated, the mean ranks of errors from CFRW and ACCREG are 2.49 and 2.44, respectively. As these ranks are not significantly different, CFRW does not perform significantly better than ACCREG when tobacco companies are removed. The mean volatility of earnings and volatility of sales for the tobacco companies removed from the sample is 0.1621 and 0.5329, respectively. This is in excess of 100% higher than the volatility of earnings (0.073) and volatility of sales (0.261) for all industries. This high volatility in the tobacco industry is somewhat surprising given the size of tobacco companies. The mean (median) total assets of tobacco firms is \$7.2 billion (\$1 billion) compared to total assets in all industries of \$1.9 billion (\$170 million). Included in the tobacco companies is Altria Group, the parent company of both Kraft and Phillip Morris. Altria Group's total assets grew from \$38 billion in 1989 to \$92 billion in 2004. Much of this growth is due to mergers and acquisitions (such as the acquisition of Nabisco in 2000 and Very Fine Products, Inc. in 2004), a factor that may weaken the cash flow predictions. However, tests show that the removal of only Altria Group from the Food and Tobacco industry (versus the removal of all tobacco companies) does not significantly affect the incremental predictive ability of ACCREG over CFRW.

Table 12 also reports that ACCREG produces significantly lower errors than ACCREV for five of 17 industries. The only industry that reports significantly lower errors for ACCREV than ACCREG is the tobacco and food industry. As in the analysis of ACCREG versus CFRW above, tobacco companies are responsible for this finding. When the tobacco companies are removed from the food industry the mean rank of forecast errors from ACCREG and ACCREV are 2.44 and 2.35 respectively, and are not significantly different. It appears the factors inherent in the tobacco industry that affected the performance of ACCREG, did not have a similar effect on ACCREV. Therefore, it appears the weakness in ACCREG is likely due to estimation problems versus a weakness in the accruals themselves. One possibility is that the underlying parameters of food companies are significantly different from those of tobacco companies. Thus pooling of these firms violates the assumption that parameters are constant across firms within the cross-sectional estimation and results in poor forecast performance of both CFREG and ACCREG. Ideally, this explanation could be explored by estimating the model across only tobacco firms. However, too few tobacco firms exist to adequately estimate the parameters. Consistent with this explanation, the next section shows that high heterogeneity of firms within an industry may lead to weaker cash flow forecasts.

6.4. Comparison of industries: food retailers versus non-durable goods wholesalers

To further study the factors that may affect the performance of the accrual-based prediction models, the food retailing industry (group #16) is compared to the non-durable goods industry (group #15). These industries were chosen for two reasons.

First, the industries are similar in that they purchase and sell non-durable goods merchandise. Second, the number of observations over which the prediction coefficients are estimated is not driving the difference in predictive ability as food retailers (21 minimum firms) have fewer observations than non-durable goods-wholesalers (36 minimum firms). Despite fewer observations, table 12, panel A reports ACCREG produces much lower forecast errors for food retailers than for non-durable goods wholesalers (the difference in forecast errors is significant at a 1% level).

The accrual model developed in section 3.1 may be more descriptive of the retail food industry than the non-durable goods – wholesale industry. Table 13 presents a comparison of descriptive statistics for the model parameters of each industry. The accrual model assumes all parameters are constant across time. In addition, the cross-sectional estimation of ACCREG assumes the parameters are constant within industries. A/R divided by sales (α), A/P and accrued expenses divided by payments to vendors (β), and inventory divided by future COGS (γ) are all significantly smaller for food retailers than for non-durable goods wholesalers. Perhaps more importantly, the standard deviation of the model parameters differs between industries. For good out-of-sample predictions, the model parameters must be both constant across time and constant across firms within an industry. The cross-sectional deviation of all five parameters is much smaller for food retailers than non-durable goods wholesalers. This is indicative of great homogeneity of firms within the retail food industry (i.e. all groceries stores operate very similarly). In addition, the standard deviation over time of the annual industry parameters (with the exception of β) is less for the food retailers than non-durable goods wholesalers. This indicates that food retailers are relatively stable compared to non-durable goods wholesalers. It appears in the case of food retailers versus non-durable goods wholesalers, that both homogeneity of firms within the industry and stability of firms across time may play a role in the performance of ACCREG.

6.5. The information provided by ACCREG regarding the future cash flow associated with actual future sales.

The analytical model in section 3.1 shows that in addition to the reversal of accruals, accruals may contain information about future sales and its effect on future cash flows. To determine the extent to which ACCREG captures the cash flow implications of actual future sales, actual future sales is substituted into ACCREG. The final accrual model shown in equation 14 was:

$$E_t[CF_{t+1}] = CF_t + \Delta AR_t - \Delta AP_t + (1-\beta)\Delta INV_t + \left[\frac{(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]}{\gamma(1-\pi)}\right] INV_t$$
$$-[(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]]S_t - (1-\beta)\gamma(1-\pi)E_t[G_{t+2}]$$

Recall that:

$$\frac{INV_t}{\gamma(1-\pi)} = E_t(S_{t+1})$$

Substituting actual S_{t+1} for $E_t[S_{t+1}]$ and actual $S_{t+2} - S_{t+1}$ for $E_t[G_{t+2}]$ modifies the model to include actual future sales:

$$E_t[CF_{t+1}] = CF_t + \Delta AR_t - \Delta AP_t + (1-\beta)\Delta INV_t + [(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]]S_{t+1}$$
$$-[(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]]S_t - (1-\beta)\gamma(1-\pi)\Delta S_{t+2}$$

where S_{t+1} is actual future sales and ΔS_{t+2} is growth in actual sales from t+1 to t+2. The above model (denoted ACCREG*) is estimated using the same alternative estimation procedures applied to ACCREG:

Accrual Regression Model with Actual Future Sales (ACCREG)*

$$E(CFO_{i,t+1}) = \theta_0 + \theta_1 CFO_{i,t} + \theta_2 \Delta AR_{i,t} + \theta_3 \Delta AP_{i,t} + \theta_4 \Delta AccExp_{i,t} - \theta_5 \Delta AccIT_{i,t} + \theta_6 \Delta INV_{i,t} + \theta_7 S_{i,t+1} + \theta_8 S_{i,t} + \theta_9 \Delta S_{i,t+2}$$

where the θ's are estimated using WLS by industry while pooling observations from years t-2 through t. The parameters are then applied to year t data to predict year t+1 cash flows. The inability of ACCREG to capture the cash flow effect of actual future sales can be measured as the absolute forecast error of ACCREG less the absolute forecast error of ACCREG*.

As a benchmark model to assess the ability of ACCREG to capture cash flow information contained in future sales, the actual sales variables S_{t+1} and ΔS_{t+2} are added to the CFREG model:

Cash Flow Regression Model with Actual Future Sales (CFREG)*

$$E(CFO_{i,t+1}) = \theta_0 + \theta_1 CFO_{i,t} + \theta_2 S_{i,t+1} + \theta_3 \Delta S_{i,t+2}$$

The inability of CFREG to capture the information contained in actual future sales can be measured as the absolute forecast error of CFREG less the absolute forecast error of CFREG*.

Table 14, panel B reports the coefficients from estimating CFREG* and ACCREG*. All coefficients are significant and in the expected direction with the exception of ΔS_{t+1} in ACCREG*. Theoretically, the growth in sales from period t to t+1 should decrease cash flows in period t due to the increase in inventory associated with the increase in sales. However, this is a small effect on cash flow and therefore it is not surprising that the WLS regression fails to pick up the effect.

Table 14, panel C reports the effect of using actual future sales in the prediction models. The use of actual future sales in CFREG* improves the absolute forecast error of CFREG by 7.5% (.0062/.0829) while the use of actual future sales in ACCREG* improves the forecast error of ACCREG by only 2% (.0015/.0768). The difference in improvement between the models of .0047 is highly significant with a t-statistic of 15.10. Since the introduction of actual future sales has a smaller effect on the absolute forecast errors of ACCREG than CFREG, ACCREG contains more information regarding the effect of actual future sales on future cash flows than CFREG. Consistent with hypothesis 2, panel D reports that the error with which ACCREG captures the effect of future sales on cash flows (i.e. ACCREG less ACCREG*) is increasing with IRVOL. However, this correlation is only marginally significant with p-value of .06.

Table 15 reports the effects of introducing actual sales in both CFREG* and ACCREG*, as well as the difference in the effect, by industry. The introduction of actual future sales in ACCREG* significantly reduces both the mean and median forecast error (compared to ACCREG) for only 4 of the 17 industries. In other words, tests for 13 industries are unable to detect any cash flow information in actual future sales incremental to the information contained in ACCREG. In contrast, the introduction of actual future sales in CFREG* significantly reduces the absolute forecast error relative to CFREG in 12 of the 17 industries. The final column reports that the introduction of actual future sales had a significantly larger impact on the CFREG model than the ACCREG model for 13 of 17 industries. Thus, ACCREG contains more information regarding the cash flow effects of actual future sales than does the CFREG model for 13 of the 17 industries. This is consistent with the notion that a portion of ACCREG's incremental predictive ability is derived from its ability to forecast future sales.

7. Conclusions

This paper finds that an accrual model in which cash flows are assumed to follow a random walk and payables and receivables are assumed to reverse in the following period predicts cash flows more accurately than a model based only on cash flows. Thus, the accrual reversal model has incremental predictive ability over cash flow only models in predicting future cash flows. The paper also finds that this incremental predictive ability is decreasing in the volatility of both earnings and cash flows.

This paper develops a more sophisticated accrual model than the accrual reversal model discussed above by building upon the model of Barth, Cram and Nelson (2001) to incorporate the cash flow implications of growth in future sales and allowing management to impound their forecasts of future sales into ending inventory. Initial results fail to find evidence that the accrual model developed in this paper has incremental predictive ability beyond that of cash flow-based models. However, supplementary analysis estimating the parameters of the accrual model while pooling observations from the prior three years shows that the model does have incremental predictive ability beyond that of both cash flow-based models and the naïve accrual model discussed above. It appears the lack of findings in Lev et. al. regarding the incremental predictive ability of accrual models is likely due to low power in their estimation of the prediction model versus large estimation errors impounded in accruals as they concluded. Consistent with the hypotheses in this paper, the incremental predictive ability of the accrual model is found to be decreasing in firm volatility and increasing in firm size. Finally, in the case of food retailers versus non-durable goods wholesalers, anecdotal evidence is found that the stability (both cross-sectional and over time) of the underlying accrual parameters significantly affects the predictive ability of the accrual model.

This paper finds that the accrual model developed contains information other than the mechanical reversal of accruals. Consistent with the model assumption that ending inventory contains information regarding future sales, evidence is found that the incremental predictive ability of the accrual model over cash flow only models is partially due to the accrual model containing information about actual future sales. Actual future sales is substituted for expected future sales in the accrual model to test the extent to which the accrual model captures the cash flow information in actual future sales. While the introduction of actual future sales does significantly decrease the absolute forecast error of the accrual model on average, tests are unable to detect any decrease in 13 of the 17 individual industries. Furthermore, this decrease in absolute forecast error is much smaller than the decrease when actual sales are included in the cash flow only model. Therefore, the accrual model contains more information regarding the future cash flow from future sales than the cash flow only model.

Finally, this paper finds that the appropriate benchmark cash flow model to assess the predictive ability of accrual models differs across firm characteristics. Some prior researchers (Bowen, Burgstahler, and Daley 1986, and Dechow, Kothari, and Watts 1998) use a random walk cash flow model while other researchers (Kim and Kross, 2005 and Lev et al. 2005) use a cash flow model where current cash flows are regressed on prior cash flows and the coefficients used to predict future cash flows. Results show that, on average, the random walk model produces lower out-of-sample forecast errors than the regression model. The superiority of the cash flow random walk over the cash flow regression is decreasing in firm volatility. In fact, for firms in the highest quartile of volatility the cash flow regression model is superior to the cash flow random walk model.

References

Barth, M., D. Cram, and K. Nelson, 2001. Accruals and the Prediction of Future Cash Flows. *The Accounting Review* 76: 27-58.

Bowen, Robert M., David Burgstahler, and Lane A. Daley, 1986. Evidence on the Relationships between Earnings and Various Measures of Cash Flow. *The Accounting Review* 61 (Oct): 713-725.

Bowen, Robert M., David Burgstahler, and Lane A. Daley, 1987. The Incremental Information Content of Accrual versus Cash flows. *The Accounting Review* 62 (Oct): 723-747.

Dechow, Patricia M., 1994. Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals. *Journal of Accounting and Economics* 18: 3-42.

Dechow, Patricia M. and Ilia D. Dichev, 2002. The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. *The Accounting Review* 77 (Supplement): 35-59.

Dechow, Patricia M., S.P. Kothari, and Ross Watts, 1998. The relation between earnings and cash flows. *Journal of Accounting and Economics* 25: 133-168.

Diebold, Francis X., and Roberto S. Mariano, 1995. Comparing Predictive Accuracy. *Journal of Business & Economic Statistics* (July): 253 – 263.

Dreyfus, Patricia, 1988. Go with the (cash) flow. *Institutional Investor* (Aug): 55 –59.

Financial Accounting Standards Board (FASB), 1978. *Objectives of Financial Reporting by Business Enterprises.* Statement of Financial Accounting Concepts No. 1. Stamford, CT: FASB.

Finger, Catherine A., 1994. The Ability of Earnings to Predict Future Earnings and Cash Flows. *Journal of Accounting Research* 32 (Autumn): 210-223.

Greene, William H., 2000. *Econometric Analysis.* Prentice Hall, Inc.

Greenberg, Robert R., Glenn L. Johnson, and K. Ramesh, 1986. Earnings versus Cash Flow as a Predictor of Future Cash Flow Measures. *Journal of Accounting, Auditing & Finance* 1 (Fall): 266-277.

Holthausen, Robert W. and Ross L. Watts, 2001. The relevance of the value-relevance literature for financial accounting standard setting. *Journal of Accounting and Economics* 31: 3-75.

Hribar, Paul and Daniel W. Collins, 2001. Errors in Estimating Accruals: Implications for Empirical Research. *Journal of Accounting Research* 40 (Mar): 105 – 134.

Institutional Investor, 1999. Reigning cash. (Aug) Vol. 33, Iss. 8: 28.

Kim, Myungsun and William Kross, 2005. The Ability of Earnings to Predict Future Operating Cash Flows Has Been Increasing – Not Decreasing. *Journal of Accounting Research* 43 (Dec): 1 – 28.

Kim, Oliver, Steve C. Lim, and Taewoo Park, 2005. The Value Relevance of Earnings and the Prediction of Future Cash Flows. Working Paper.

Lev, Baruch, Siyi Li, and Theodore Sougiannis, 2005. Accounting Estimates: Pervasive, Yet of Questionable Usefulness. Working Paper.

Lipe, Robert C., 1986. The Information Contained in the Components of Earnings. *Journal of Accounting Research* 24 (Studies on Alternative Measures of Accounting Income): 37 – 64.

Lo, Kin, 2005. The Effects of Scale Differences on Inferences in Accounting Research: Coefficient Estimates, Tests of Incremental Association, and Relative Value Relevance. The University of British Columbia. Working Paper.

Lorek, Kenneth S., and G. Lee Willinger, 1996. A Multivariate Time-Series Prediction Model for Cash flow Data. *The Accounting Review* 71 (Jan): 81 – 102.

Neter, John, Michael H. Kutner, Christopher J. Nachtsheim, and William Wasserman, 1996. *Applied Linear Statistical Models.* WCB/McGraw-Hill.

Rayburn, Judy, 1986. The Association of Operating Cash Flow and Accruals with Security Returns. *Journal of Accounting Research* 24 (Studies on Alternative Measures of Accounting Income): 112-133.

Studenmund, A. H., 1997. *Using Econometrics: A Practical Guide*. Addison-Wesley Educational Publishers.

Wilson, G. Peter, 1986. The Relative Information Content of Accruals and Cash Flows: Combined Evidence at the Earnings Announcement and Annual Report Release Date. *Journal of Accounting Research* 24 (Studies on Alternative Measures of Accounting Income): 165 – 200.

Table 1
Variable Definitions

Variable	Definition
CFO	Cash flow from operations.
ΔAR	Change in accounts receivable (net).*
ΔInv	Change in inventory.*
ΔAP	Change in accounts payable.*
ΔAccExp	Change in accrued expense.*
ΔAccIT	Change in accrued income tax payable.*
Inv	Level of ending inventory.
S	Annual sales (net).
G	Growth in sales calculated $S_t - S_{t-1}$.
AvgTA	Beginning plus ending total assets divided by two.
IRVOL	Volatility of the ratio of ending inventory to next period sales measured as the firm specific standard deviation of INV_t/S_{t+1} over all sample years.
SALESVOL	Volatility of sales measured as the firm-specific standard deviation of $S_t/AvgTA_t$ over all sample years.
EARNVOL	Volatility of earnings measured as the firm-specific standard deviation of income before extraordinary items scaled by average total assets over all sample years.
α	Ratio of year-end accounts receivable to sales.
β	Ratio of year-end accounts payable to inventory purchases plus operating expenses.
γ	Fraction of next period's cost of goods sold (COGS) included in ending inventory measured as $INV_t/COGS_{t+1}$.
π	Gross profit percentage measured as $(S_t - COGS_t)/S_t$.
λ	Ratio of operating expenses (OE) to sales measured as OE_t/S_t.

* The change in accruals is taken from the statement of cash flows when available. If not available, the change is calculated as the difference between the current accrual and the prior period accrual. With the exception of ΔAccIT, if the statement of cash flow information is not available and either the current or prior period accrual is missing, the observation is discarded. If information is not available for ΔAccIT, the variable ΔAccIT for that observation is set to zero.

Table 2 (page 1 of 3)
Descriptive Statistics for Sample of Firms

Panel A: Distribution of Financial Statement Variables (Millions)

Variable	Median	Mean	Standard Deviation
CFO	10.116	189.119	907.772
ΔAR	0.957	11.189	199.925
ΔInv	0.608	6.802	108.992
ΔAP	0.167	4.458	189.445
ΔAccExp	0.374	9.811	145.237
ΔAccIT	0.000	1.232	63.757
Inv	31.975	233.124	846.125
S	216.021	2112.260	8911.100
AvgTA	170.334	1901.510	9016.030

Panel B: Correlations of Financial Statement Variables scaled by Avg. Total Assets

	CFO	ΔAR	ΔInv	ΔAP	ΔAccExp	ΔAccIT	Inv	Sales
CFO	--	-0.1481 *<.01*	-0.2098 *<.01*	0.0296 *<.01*	0.0818 *<.01*	0.1842 *<.01*	-0.1564 *<.01*	0.0757 *<.01*
ΔAR	-0.1137 *<.01*	--	0.3262 *<.01*	0.4059 *<.01*	0.1887 *<.01*	0.1316 *<.01*	0.0903 *<.01*	0.1094 *<.01*
ΔInv	-0.1778 *<.01*	0.3249 *<.01*	--	0.3566 *<.01*	0.1457 *<.01*	0.0406 *<.01*	0.3125 *<.01*	0.1049 *<.01*
ΔAP	0.0490 *<.01*	0.3630 *<.01*	0.2963 *<.01*	--	-0.1512 *<.01*	0.0605 *<.01*	0.1128 *<.01*	0.1079 *<.01*
ΔAccExp	0.1271 *<.01*	0.2368 *<.01*	0.1788 *<.01*	-0.036 *<.01*	--	0.0595 *<.01*	0.0551 *<.01*	0.0382 *<.01*
ΔAccIT	0.1619 *<.01*	0.1419 *<.01*	0.0529 *<.01*	0.0979 *<.01*	0.0950 *<.01*	--	-0.0103 *0.10*	0.0209 *<.01*
Inv	-0.1710 *<.01*	0.1020 *<.01*	0.2571 *<.01*	0.0775 *<.01*	0.0643 *<.01*	-0.0162 *<.01*	--	0.3959 *<.01*
S	0.1289 *<.01*	0.1543 *<.01*	0.1214 *<.01*	0.1136 *<.01*	0.0990 *<.01*	0.0205 *<.01*	0.5073 *<.01*	--

Correlations above (below) the diagonal are Pearson (Spearman) correlations. The bottom number in each cell is a two-tail p-value. CFO is cash flow from operations. ΔAR is change in accounts receivable (net). ΔInv is change in inventory. ΔAP is change in accounts payable. ΔAccExp is change in accrued expense. ΔAccIT is change in accrued income tax. Inv is the level of ending inventory. S is sales. AvgTA is average total assets.

Table 2 (page 2 of 3)
Descriptive Statistics for Sample Firms

Panel C: Distribution of firm parameters and firm characteristics

Variable	Median	Mean	Standard Deviation
α	0.158	0.168	0.0937
β	0.152	0.161	0.0681
γ	0.242	0.302	0.5667
π	0.338	0.364	0.1819
λ	0.252	0.311	0.2671
IRVOL	0.034	0.055	0.1033
SALESVOL	0.211	0.261	0.2066
EARNVOL	0.055	0.073	0.0589

Reported statistics relate to the distribution of firm specific parameters and characteristics across firms. **α** is the ratio of ending accounts receivable to annual sales. **β** is the ratio of accounts payable to annual inventory purchases plus operating expenses. **γ** is the fraction of next period's cost of goods sold included in ending inventory. **π** is the gross profit percentage. **λ** is the ratio of operating expenses to sales. **IRVOL** is the firm specific standard deviation of the ratio of ending inventory to next period's sales. **SALESVOL** is the firm specific standard deviation of sales. **EARNVOL** is the firm specific standard deviation of earnings.

Table 2 (page 3 of 3)
Descriptive Statistics for Sample Firms

Panel D: Correlations of parameters and firm characteristics

	α	**β**	**γ**	**π**	**λ**	**IRVOL**	**AVGTA**	**SALESVOL**	**EARNVOL**
α	--	0.3707 *<.01*	0.1041 *<.01*	0.2073 *<.01*	0.1969 *<.01*	0.1364 *<.01*	0.0657 *<.01*	-0.2053 *<.01*	0.0748 *<.01*
β	0.3983 *<.01*	--	0.0990 *<.01*	0.1572 *<.01*	0.1522 *<.01*	0.1053 *<.01*	0.0959 *<.01*	-0.1699 *<.01*	0.07210 *<.01*
γ	0.3329 *<.01*	0.1766 *<.01*	--	0.1130 *<.01*	0.1707 *<.01*	0.5321 *<.01*	-0.0300 *0.07*	-0.1308 *<.01*	0.1529 *<.01*
π	0.3037 *<.01*	0.1915 *<.01*	0.4111 *<.01*	--	0.5248 *<.01*	-0.0220 *0.30*	-0.0231 *0.16*	-0.2243 *<.01*	0.15730 *<.01*
λ	0.3054 *<.01*	0.1777 *<.01*	0.4925 *<.01*	0.7999 *<.01*	--	0.1825 *<.01*	-0.0712 *<.01*	-0.0598 *<.01*	0.3918 *<.01*
IRVOL	0.3041 *<.01*	0.1830 *<.01*	0.6173 *<.01*	0.0364 *0.09*	0.2146 *<.01*	--	-0.0483 *0.02*	0.0905 *<.01*	0.2214 *<.01*
AVGTA	-0.0578 *<.01*	0.2467 *<.01*	-0.2136 *<.01*	-0.0544 *<.01*	-0.2862 *<.01*	-0.3355 *<.01*	--	-0.0814 *<.01*	-0.1110 *<.01*
SALESVOL	-0.1736 *<.01*	-0.1427 *<.01*	-0.1623 *<.01*	-0.2105 *<.01*	-0.0359 *0.09*	0.2230 *<.01*	-0.2353 *<.01*	--	0.3483 *<.01*
EARNVOL	0.1267 *<.01*	0.0717 *<.01*	0.2035 *<.01*	0.1525 *<.01*	0.3221 *<.01*	0.4657 *<.01*	-0.4476 *<.01*	0.4695 *<.01*	--

Figures in italics are two-tailed p-values. Correlations above (below) the diagonal are Pearson (Spearman) correlations. **α** is the ratio of ending accounts receivable to annual sales. **β** is the ratio of accounts payable to annual inventory purchases plus operating expenses. **γ** is the fraction of next period's cost of goods sold included in ending inventory. ***π*** is the gross profit percentage. **λ** is the ratio of operating expenses to sales. **IRVOL** is the firm specific standard deviation of the ratio of ending inventory to next period's sales. **SALESVOL** is the firm specific standard deviation of sales. **EARNVOL** is the firm specific standard deviation of earnings.

Table 3 (page 1 of 2)
Cash Flow Predictions

Panel A: Prediction Models

Cash flow-based random walk model (CFRW):

$$E(CFO_{i,t+1}) = CFO_{i,t}$$

Cash flow-based regression model (CFREG):

$$E(CFO_{i,t+1}) = \theta_0 + \theta_1 CFO_{i,t}$$

Accrual-based reversal model (ACCREV):

$$E(CFO_{i,t+1}) = CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t}$$

Accrual-based parameter model (ACCPAR):

$$E(CFO_{i,t+1}) = CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t} + (1-\beta)\Delta INV_{i,t}$$
$$+ \left[\frac{(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]}{\gamma(1-\pi)}\right] INV_{i,t} - [(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]]S_{i,t}$$
$$-(1-\beta)\gamma(1-\pi)E\Delta Sales2_{i,t}$$

Accrual-based regression model (ACCREG):

$$E(CFO_{i,t+1}) = \theta_0 + \theta_1 CFO_{i,t} + \theta_2 \Delta AR_{i,t} - \theta_3 \Delta AP_{i,t} - \theta_4 \Delta AccExp_{i,t} - \theta_5 \Delta AccIT_{i,t} +$$
$$\theta_6 \Delta INV_{i,t} + \theta_7 INV_{i,t} + \theta_8 S_{i,t} + \theta_9 E\Delta Sales2_{i,t}$$

The θ parameters in models CFREG and ACCREG are estimated with weighted least squares regressions (weighted by average total assets) within industry and year by regressing year t cash flow on year t-1 observations of the independent variables. The parameters in ACCPAR (i.e. α, β, γ, π, and λ) are calculated separately for each firm as the average parameters over the year t, t-1 and t-2. α is the ratio of ending accounts receivable to annual sales. β is the ratio of accounts payable to annual inventory purchases plus operating expenses. γ is the fraction of next period's cost of goods sold included in ending inventory. π is the gross profit percentage. λ is the ratio of operating expenses to sales. CFO is cash flow from operations. ΔAR is change in accounts receivable (net). ΔAP is change in accounts payable. ΔAccExp is change in accrued expense. ΔAccIT is change in accrued income tax. ΔInv is change in inventory. Inv is the level of ending inventory. S is sales. EΔSales2 is the expected change in two period ahead sales.

Table 3 (page 2 of 2)
Cash Flow Predictions

Panel B: Coefficient Estimates

	CFREG		ACCPAR		ACCREG	
	Coef	*t-stat*	Coef	*t-stat*	Coef	*t-stat*
Intercept	.2720	*2.51*			-.3548	*-3.74*
CFO_{t-1}	.7476	*45.31*	1.0*		.6849	35.39
ΔAR_{t-1}			1.0*		.4639	*15.47*
ΔAP_{t-1}			1.0*		-.4868	*-17.43*
$\Delta AccExp_{t-1}$			1.0*		-.2858	*-6.69*
$\Delta AccIT_{t-1}$			1.0*		-.4915	*-8.84*
ΔINV_{t-1}			.8425	*432.95*	.3288	*11.54*
INV_{t-1}			1.1085	*22.31*	-.0227	*-2.18*
S_{t-1}			-.0575	*-17.46*	*.0255*	*12.45*
$E\Delta Sales2_{t-1}$			-.1060	*-66.98*	-.0067	*-1.80*
R^2	.4858		N/A		.6236	

* Constrained to equal one.

Panel C: Absolute Out-of-Sample Forecast Errors

	Cash Flow Forecast Error Scaled by AvgTA		Cash Flow Forecast Error Scaled by Absolute Cash Flow*	
Model	**Mean**	**Median**	**Mean**	**Median**
CFRW	.0768	.0493	.5662	.5283
CFREG	.0785	.0538	.5994	.5999
ACCREV	.0753	.0481	.5571	.5082
ACCPAR	.1193	.0736	.6706	.8003
ACCREG	.0807	.0535	.5828	.5592

*Cash flow forecast errors scaled by absolute cash flow from operations are windsorized at 1. Observations where cash flow from operations equals zero are omitted from the mean and median calculation.

Figures in italics are t-statistics. Models CFREG and ACCREG estimated with weighted least squares regressions (weighted by average total assets) within industry and year by regressing year t cash flow on year t-1 observations of the independent variables. The coefficients reported are the mean coefficients across all industries and years. The coefficients in ACCPAR are calculated by individual parameter (i.e. α, β, γ, π, and λ) as detailed in panel A. CFO is cash flow from operations. ΔAR is change in accounts receivable (net). ΔAP is change in accounts payable. ΔAccExp is change in accrued expense. ΔAccIT is change in accrued income tax. ΔInv is change in inventory. Inv is the level of ending inventory. S is sales. EΔSales2 is the expected change in sales from period t to t+1. The expected change in sales is computed based on the growth in sales from period t-2 to period t-1. See section 3.2.2 for a discussion of this approach.

Table 4
ANOVA on Absolute Forecast Errors

Panel A: Significance of Models in Explaining Rank of Forecast Error within Firm-years.

	F-Test	**Friedman χ^2**
Statistic	625.35	2,430.94
p-value	(<.01)	(<.01)

Panel B: Bonferonni Pairwise Comparisons of Models

Min. Significant Difference	**.0428***	
Model	**Mean Rank across Firm-Years**	**Grouping****
ACCREV	2.7495	A
CFRW	2.8533	B
ACCREG	2.9470	C
CFREG	3.0085	D
ACCPAR	3.4417	E

A rank ANOVA was performed by first ranking the forecast errors generated by each model within each firm year. The lowest absolute forecast error was given rank 1 and the largest absolute forecast error was given rank 5. The ANOVA was then run as a complete block design where each block consisted of exactly one firm-year treated under each of the five forecast models. (See Neter et. al., page 1094 for a discussion of this methodology.)

*The minimum significant difference between mean ranks was calculated using a Bonferonni procedure adapted for rank ANOVAs with large sample sizes. (See Neter et. al., page 1096 for a discussion.)

**Models with the same group letter are not significantly different from each other.

Table 5 (page 1 of 2)
Effect of Firm Characteristics on Prediction Models

Panel A: Spearman correlation between median firm-specific forecast errors (scaled by average total assets) and firm characteristics

	IRVOL		EARNVOL		SALESVOL		AVGTA	
CFRW	?	0.3722 (<.01)	+	0.5310 [<.01]	+	0.3350 [<.01]	?	-0.4622 (<.01)
CFREG	?	0.2638 (<.01)	+	0.4765 [<.01]	+	0.2926 [<.01]	?	-0.3904 (<.01)
ACCREV	?	0.3860 (<.01)	+	.5507 [<.01]	+	0.3457 [<.01]	?	-0.4511 (<.01)
ACCPAR	+	0.2112 [<.01]	+	0.4495 [<.01]	+	0.2296 [<.01]	-	-0.2825 [<.01]
ACCREG	+	0.3634 [<.01]	+	0.5380 [<.01]	+	0.3409 [<.01]	-	-0.4445 [<.01]

Predicted signs are given to the left of the correlation coefficient. Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. IRVOL is the firm-specific standard deviation of Inventory divided by one-period-ahead sales. EARNVOL is the firm-specific standard deviation of earnings scaled by average total assets. SALESVOL is the firm-specific standard deviation of sales scaled by average total assts. AVGTA is average total assets.

Table 5 (page 2 of 2)
Effect of Firm Characteristics on Prediction Models

Panel B: Spearman correlation between median firm-specific incremental predictive abilities (scaled by average total assets) and firm characteristics

	IRVOL		EARNVOL		SALESVOL		AVGTA	
CFRW less CFREG	?	0.2636 (<.01)	?	0.1889 (<.01)	?	0.1322 (<.01)	?	-0.1892 (<.01)
CFRW less ACCREV	?	0.0115 (.59)	?	0.0174 (.41)	?	0.0350 (.10)	?	-0.0451 (<.01)
CFRW less ACCPAR	-	0.0759 [>.99]	?	-0.0552 (<.01)	?	0.0417 (.05)	+	-0.0654 [>.99]
CFRW less ACCREG	-	0.0246 [.88]	?	0.0014 (.95)	?	0.0113 (.60)	+	-0.0247 [.93]
CFREG less ACCREV	?	-0.1798 (<.01)	?	-0.1238 (<.01)	?	-0.0870 (<.01)	?	0.0888 (<.01)
CFREG less ACCPAR	-	-0.0243 [.13]	?	-0.109 (<.01)	?	-0.0108 (.61)	+	-0.0026 [.56]
CFREG less ACCREG	-	-0.1514 [<.01]	?	-.0949 (<.01)	?	-0.0772 (<.01)	+	0.0834 [<.01]
ACCREV less ACCREG	-	0.0680 [>.99]	?	0.0414 (.05)	?	0.0221 (.30)	+	-0.0103 [.73]

Predicted signs are given to the left of the correlation coefficient. Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. IRVOL is the firm-specific standard deviation of Inventory divided by one-period-ahead sales. EARNVOL is the firm-specific standard deviation of earnings scaled by average total assets. SALESVOL is the firm-specific standard deviation of sales scaled by average total assts. AVGTA is average total assets.

Table 6 (page 1 of 4)
Incremental Predictive Ability by Quartiles of Firm Characteristics

Panel A: Volatility of Inventory Ratio (IRVOL)

Models Compared	All Firms**		Quartile 1		Quartile 2		Quartile 3		Quartile 4	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
CFRW less CFREG (?)	-.0001 (.55)	-.0018 (<.01)	-.0007 (<.01)	-.0005 (<.01)	-.0010 (<.01)	-.0016 (<.01)	.0020 (<.01)	.0005 (.28)	.0097* (<.01)	.0050 (<.01)
CFRW less ACCREV (?)	.0015 [<.01]	.0018 [<.01]	.0022 [<.01]	.0016 [<.01]	.0016 [<.01]	.0019 [<.01]	.0007 [.18]	.0017 [<.01]	.0027 [<.01]	.0026 [<.01]
CFRW less ACCPAR (-)	-.0425 [>.99]	-.0167 [>.99]	-.0451 [>.99]	-.0239 [>.99]	-.0368 [>.99]	-.0152 [>.99]	-.0331 [>.99]	-.0128 [>.99]	-.0337 [>.99]	-.0130 [>.99]
CFRW less ACCREG (-)	.0062 [<.01]	.0031 [<.01]	.0036 [<.01]	.0023 [<.01]	.0041 [<.01]	.0016 [<.01]	.0073 [<.01]	.0044 [<.01]	.0121 [<.01]	.0079 [<.01]
CFREG less ACCREV (?)	.0016 [<.01]	.0048 [<.01]	.0029 [<.01]	.0030 [<.01]	.0026 [<.01]	.0035 [<.01]	-.0012 [.93]	.0018 [<.01]	-.0070* [>.99]	-.0031 [>.99]
CFREG less ACCPAR (-)	-.0424 [>.99]	-.0157 [>.99]	-.0444 [>.99]	-.0251 [>.99]	-.0358 [>.99]	-.0142 [>.99]	-.0350 [>.99]	-.0130 [>.99]	-.0435 [>.99]	-.0190 [>.99]
CFREG less ACCREG (-)	.0063** [<.01]	.0074 [<.01]	.0043 [<.01]	.0032 [<.01]	.0051 [>.99]	.0047 [<.01]	.0054 [<.01]	.0061 [<.01]	.0024* [<.01]	.0032 [<.01]
ACCREV less ACCREG (-)	.0047 [<.01]	.0017 [<.01]	.0013 [<.01]	.0007 [.02]	.0025 [<.01]	.0006 [.04]	.0066 [<.01]	.0028 [<.01]	.0094 [<.01]	.0055 [<.01]

CFREG and ACCREG are estimated within quartiles and year (except for the "All Firms" column). The top figure in each cell is the difference in absolute error (scaled by average total assets) between the two models listed in the first column. A positive value indicates the second model listed produces a lower error than the first. Figures in parenthesis are two-tailed p-values and figures in brackets are one-tailed p-values. P-values for means are based on a paired t-test and p-values for medians are based on a non-parametric sign test. The predicted direction of change across quartiles is given in parenthesis following the title of each row.

* indicates the difference in means between the fourth and first quartile is significant in the predicted direction at the 5% level using a pooled t-test.

** Errors reported for "All Firms" are from estimating the models over all firm years with no control for either industry or firm characteristics. The fact that CFREG less ACCREG for "All Firms" is higher than the average CFREG less ACCREG across quartiles is evidence that ACCREG is more powerful when estimated across all firms versus within quartiles of IRVOL.

Table 6 (page 2 of 4)
Incremental Predictive Ability by Quartiles of Firm Characteristics

Panel B: Earnings Volatility (EARNVOL)

Models Compared	All Firms**		Quartile 1		Quartile 2		Quartile 3		Quartile 4	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
CFRW less CFREG (?)	-.0001 (.55)	-.0018 (<.01)	-.0008 (<.01)	-.0017 (<.01)	-.0004 (0.24)	-.0018 (<.01)	.0005 (.29)	-.0003 (.68)	.0050* (<.01)	.0042 (<.01)
CFRW less ACCREV (?)	.0015 [<.01]	.0018 [<.01]	.0013 [<.01]	.0012 [<.01]	.0036 [<.01]	.0028 [<.01]	.0009 [.12]	.0016 [<.01]	.0013 [.13]	.0028 [<.01]
CFRW less ACCPAR (?)	-.0425 [>.99]	-.0167 [>.99]	-.0299 [>.99]	-.0177 [>.99]	-.0244 [>.99]	-.0127 [>.99]	-.0372 [>.99]	-.0157 [>.99]	-.0590* [>.99]	-.0217 [>.99]
CFRW less ACCREG (?)	.0062 [<.01]	.0031 [<.01]	.0039 [<.01]	.0025 [<.01]	.0063 [<.01]	.0035 [<.01]	.0060 [<.01]	.0032 [<.01]	.0083* [<.01]	.0064 [<.01]
CFREG less ACCREV (?)	.0016 [<.01]	.0048 [<.01]	.0021 [<.01]	.0024 [<.01]	.0040 [<.01]	.0052 [<.01]	.0004 [.31]	.0023 [<.01]	-.0037* [>.99]	-.0006 [.72]
CFREG less ACCPAR (?)	-.0424 [>.99]	-.0157 [>.99]	-.0291 [>.99]	-.0173 [>.99]	-.0240 [>.99]	-.0115 [>.99]	-.0377 [>.99]	-.0158 [>.99]	-.0640* [>.99]	-.0255 [>.99]
CFREG less ACCREG (?)	.0063** [<.01]	.0074 [<.01]	.0047 [<.01]	.0040 [<.01]	.0067 [<.01]	.0063 [<.01]	.0055 [<.01]	.0056 [<.01]	.0033 .[<.01]	.0050 [<.01]
ACCREV less ACCREG (?)	.0047 [<.01]	.0017 [<.01]	.0026 [<.01]	.0013 [<.01]	.0027 [<.01]	.0008 [.02]	.0050 [<.01]	.0024 [<.01]	.0070* [<.01]	.0047 [<.01]

CFREG and ACCREG are estimated within quartiles and year (except for the "All Firms" column). The top figure in each cell is the difference in absolute error (scaled by average total assets) between the two models listed in the first column. A positive value indicates the second model listed produces a lower error than the first. Figures in parenthesis are two-tailed p-values and figures in brackets are one-tailed p-values. P-values for means are based on a paired t-test and p-values for medians are based on a non-parametric sign test.

* indicates the difference in means between the fourth and first quartile is significant using a pooled t-test.

** Errors reported for "All Firms" are from estimating the models over all firm years with no control for either industry or firm characteristics. The fact that CFREG less ACCREG for "All Firms" is higher than the average CFREG less ACCREG across quartiles is evidence that ACCREG is more powerful when estimated across all firms versus within quartiles of EARNVOL.

Table 6 (page 3 of 4)
Incremental Predictive Ability by Quartiles of Firm Characteristics

Panel C: Sales Volatility (SALESVOL)

Models Compared	All Firms**		Quartile 1		Quartile 2		Quartile 3		Quartile 4	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
CFRW less CFREG (?)	-.0001 (.55)	-.0018 (<.01)	-.0007 (<.01)	-.0016 (<.01)	-.0010 (<.01)	-.0022 (<.01)	-.0002 (.62)	-.0013 (<.01)	.0049* (<.01)	.0022 (<.01)
CFRW less ACCREV (?)	.0015 [<.01]	.0018 [<.01]	.0009 [.06]	.0013 [<.01]	.0032 [<.01]	.0024 [<.01]	.0010 [.08]	.0021 [<.01]	.0020 [.03]	.0021 [<.01]
CFRW less ACCPAR (?)	-.0425 [>.99]	-.0167 [>.99]	-.0372 [>.99]	-.0200 [>.99]	-.0321 [>.99]	-.0134 [>.99]	-.0379 [>.99]	-.0168 [>.99]	-.0411 [>.99]	-.0148 [>.99]
CFRW less ACCREG (?)	.0062 [<.01]	.0031 [<.01]	.0036 [<.01]	.0020 [<.01]	.0054 [<.01]	.0030 [<.01]	.0038 [<.01]	.0020 [<.01]	.0097* [<.01]	.0053 [<.01]
CFREG less ACCREV (?)	.0016 [<.01]	.0048 [<.01]	.0016 [<.01]	.0027 [<.01]	.0042 [<.01]	.0056 [<.01]	.0013 [.06]	.0041 [<.01]	-.0029* [>.99]	.0018 [.04]
CFREG less ACCPAR (?)	-.0424 [>.99]	-.0157 [>.99]	-.0364 [>.99]	-.0195 [>.99]	-.0311 [>.99]	-.0114 [>.99]	-.0377 [>.99]	-.0162 [>.99]	-.0460* [>.99]	-.0174 [>.99]
CFREG less ACCREG (?)	.0063** [<.01]	.0074 [<.01]	.0043 [<.01]	.0036 [<.01]	.0064 [<.01]	.0065 [<.01]	.0040 [<.01]	.0049 [<.01]	.0048 [<.01]	.0068 [<.01]
ACCREV less ACCREG (?)	.0047 [<.01]	.0017 [<.01]	.0028 [<.01]	.0012 [<.01]	.0022 [<.01]	.0009 [<.01]	.0028 [<.01]	.0005 [.18]	.0076* [<.01]	.0038 [<.01]

CFREG and ACCREG are estimated within quartiles and year (except for the "All Firms" column). The top figure in each cell is the difference in absolute error (scaled by average total assets) between the two models listed in the first column. A positive value indicates the second model listed produces a lower error than the first. Figures in parenthesis are two-tailed p-values and figures in brackets are one-tailed p-values. P-values for means are based on a paired t-test and p-values for medians are based on a non-parametric sign test.

* indicates the difference in means between the fourth and first quartile is significant using a pooled t-test.

** Errors reported for "All Firms" are from estimating the models over all firm years with no control for either industry or firm characteristics. The fact that CFREG less ACCREG for "All Firms" is higher than the average CFREG less ACCREG across quartiles is evidence that ACCREG is more powerful when estimated across all firms versus within quartiles of SALESVOL.

Table 6 (page 4 of 4)
Incremental Predictive Ability by Quartiles of Firm Characteristics

Panel D: Average Total Assets (AVGTA)

Models Compared	All Firms**		Quartile 1		Quartile 2		Quartile 3		Quartile 4	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
CFRW less CFREG (?)	-.0001 (.55)	-.0018 (<.01)	.0098 (<.01)	.0071 (<.01)	.0060 (<.01)	.0045 (<.01)	.0025 (<.01)	.0016 (<.01)	.0001* (.79)	.0001 (.73)
CFRW less ACCREV (?)	.0015 [<.01]	.0018 [<.01]	.0015 [.12]	.0028 [<.01]	.0039 [<.01]	.0035 [<.01]	.0014 [.02]	.0022 [<.01]	-.0001 [.54]	.0007 [<.01]
CFRW less ACCPAR (+)	-.0425 [>.99]	-.0167 [>.99]	-.0421 [>.99]	-.0119 [>.99]	-.0450 [>.99]	-.0116 [>.99]	-.0371 [>.99]	-.0146 [>.99]	-.0454 [>.99]	-.0232 [>.99]
CFRW less ACCREG (+)	.0062 [<.01]	.0031 [<.01]	.0125 [<.01]	.0086 [<.01]	.0083 [<.01]	.0056 [<.01]	.0056 [<.01]	.0035 [<.01]	.0024 [<.01]	.0012 [<.01]
CFREG less ACCREV (?)	.0016 [<.01]	.0048 [<.01]	-.0083 [>.99]	-.0033 [>.99]	-.0022 [>.99]	-.0001 [.59]	-.0011 [.94]	.0013 [.02]	-.0001* [.60]	.0012 [<.01]
CFREG less ACCPAR (+)	-.0424 [>.99]	-.0157 [>.99]	-.0518 [>.99]	-.0185 [>.99]	-.0510 [>.99]	-.0056 [>.99]	-.0400 [>.99]	-.0162 [>.99]	-.0454* [>.99]	-.0231 [>.99]
CFREG less ACCREG (+)	.0063** [<.01]	.0074 [<.01]	.0027 [<.01]	.0032 [<.01]	.0022 [<.01]	.0028 [<.01]	.0031 [<.01]	.0031 [<.01]	.0024 [<.01]	.0020 [<.01]
ACCREV less ACCREG (+)	.0047 [<.01]	.0017 [<.01]	.0110 [<.01]	.0083 [<.01]	.0044 [<.01]	.0022 [<.01]	.0042 [<.01]	.0022 [<.01]	.0025 [<.01]	.0011 [<.01]

CFREG and ACCREG are estimated within quartiles and year (except for the "All Firms" column). The top figure in each cell is the difference in absolute error (scaled by average total assets) between the two models listed in the first column. A positive value indicates the second model listed produces a lower error than the first. Figures in parenthesis are two-tailed p-values and figures in brackets are one-tailed p-values. P-values for means are based on a paired t-test and p-values for medians are based on a non-parametric sign test.
* indicates the difference in means between the fourth and first quartile is significant using a pooled t-test.
** Errors reported for "All Firms" are from estimating the models over all firm years with no control for either industry or firm characteristics. The fact that CFREG less ACCREG for "All Firms" is higher than the average CFREG less ACCREG across quartiles is evidence that ACCREG is more powerful when estimated across all firms versus within quartiles of AVGTA.

Table 7 (page 1 of 5)
Cash Flow Predictions by Industry

Panel A: Absolute Cash Flow Forecast Errors (scaled by average total assets)

		CFRW		CFREG		ACCREV		ACCPAR		ACCREG	
SIC	**Industry**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
20	Food	.0603	.0359	.0642	.0452	.0581	.0334	.1036	.0813	.0600	.0380
23	Apparel	.1002	.0678	.1042	.0865	.0897	.0577	.1072	.0784	.1175	.0814
25	Furniture	.0550	.0388	.0575	.0416	.0538	.0405	.0733	.0544	.0648	.0512
26	Paper	.0459	.0309	.0520	.0374	.0435	.0271	.0832	.0627	.0524	.0357
27	Printing	.0550	.0358	.0589	.0401	.0541	.0328	.1072	.0644	.0620	.0389
28	Chemicals	.0581	.0355	.0616	.0435	.0552	.0335	.1071	.0683	.0586	.0398
283	Pharmaceutical	.0804	.0531	.0840	.0588	.0818	.0482	.2522	.1326	.0905	.0587
29	Petro Refining	.0424	.0318	.0487	.0371	.0428	.0308	.0652	.0437	.0592	.0423
308	Plastics	.0535	.0383	.0545	.0411	.0511	.0350	.0788	.0582	.0611	.0424
33	Primary Metal	.0626	.0461	.0615	.0485	.0614	.0444	.0819	.0545	.0731	.0559
331	Steel Work	.0574	.0428	.0571	.0451	.0563	.0406	.0643	.0526	.0565	.0423
34	Fabr. Metal	.0589	.0422	.0605	.0453	.0587	.0410	.0781	.0561	.0557	.0418
35	Other Comm. Mach.	.0592	.0410	.0620	.0440	.0550	.0372	.0784	.0559	.0619	.0446
353	Manuf. Mach.	.0742	.0465	.0781	.0506	.0810	.0495	.0976	.0622	.0904	.0595
355	Spec. Ind. Mach.	.0910	.0624	.0858	.0642	.0924	.0656	.1278	.0878	.0955	.0730
356	Gen. Ind. Mach.	.0570	.0360	.0638	.0452	.0600	.0398	.0810	.0516	.0756	.0466

Table 7 (page 2 of 5)
Cash Flow Predictions by Industry

Panel A: Absolute Cash Flow Forecast Errors (scaled by average total assets) cont.

		CFRW		CFREG		ACCREV		ACCPAR		ACCREG	
SIC	**Industry**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
357	Computer Equip.	.1178	.0814	.1189	.0872	.1176	.0800	.1673	.0974	.1222	.0877
36	Electr. Equip.	.0749	.0505	.0746	.0530	.0722	.0489	.0945	.0611	.0773	.0523
366	Communication. Eq.	.1119	.0789	.1076	.0769	.1107	.0745	.1468	.0966	.1091	.0791
367	Electronics	.0967	.0665	.1010	.0733	.0934	.0650	.1351	.0886	.1005	.0696
37	Trans. Equip.	.0601	.0426	.0644	.0479	.0584	.0393	.0918	.0614	.0666	.0470
371	Motor Vehicles	.0695	.0454	.0736	.0546	.0633	.0446	.0882	.0583	.0730	.0482
38	Meas. Instr.	.0759	.0510	.0817	.0559	.0737	.0505	.1086	.0812	.0935	.0636
382	Lab Instruments	.0831	.0577	.0849	.0626	.0801	.0541	.1290	.0847	.0799	.0578
384	Medical Instr.	.0910	.0567	.0915	.0610	.0881	.0567	.1766	.0963	.0923	.0599
39	Misc. Manuf.	.0924	.0689	.0958	.0735	.0880	.0649	.1562	.0858	.0969	.0732
50	Whsle-Durable Gds	.0839	.0602	.0765	.0603	.0824	.0564	.1043	.0665	.0779	.0552
504	Whsle – Equip.	.0979	.0736	.0907	.0652	.0930	.0657	.1082	.0702	.1089	.0789
51	Whsle- Nondur. Gds.	.0846	.0554	.0912	.0649	.0847	.0537	.1159	.0645	.0980	.0632
541	Grocery Stores	.0382	.0271	.0410	.0293	.0403	.0298	.0899	.0809	.0443	.0308
59	Misc. Retail	.0799	.0522	.0774	.0576	.0867	.0588	.1496	.1105	.0734	.0521

Table 7 (page 3 of 5)
Cash Flow Predictions by Industry
Panel B: Bonferonni Pairwise Comparisons of Mean Ranks by Industry

SIC		Min. Sign. Diff.*	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**
20	Food	.1879	ACCREV 2.5854 A	CFRW 2.7661 B	ACCREG 2.8104 B	CFREG 3.0957 C	ACCPAR 3.7424 D
23	Apparel	.2952	ACCREV 2.6777 A	CFRW 2.9558 A, B	CFREG 3.0684 B	ACCPAR 3.0861 B	ACCREG 3.2119 B
25	Furniture	.3150	ACCREV 2.7613 A	CFRW 2.8593 A	CFREG 2.9221 A, B	ACCREG 3.1859 B, C	ACCPAR 3.2714 C
26	Paper	.2625	ACCREV 2.4415 A	CFRW 2.7103 B	ACCREG 3.0401 C	CFREG 3.1658 C, D	ACCPAR 3.6422 D
27	Printing	.2453	ACCREV 2.6082 A	CFRW 2.7088 A	ACCREG 3.0061 B	CFREG 3.0473 B	ACCPAR 3.6296 C
28	Chemicals	.1776	ACCREV 2.6259 A	ACCREG 2.7722 A, B	CFRW 2.7994 B	CFREG 3.1015 C	ACCPAR 3.7010 D
283	Pharmaceutical	.2188	ACCREV 2.6115 A	CFRW 2.6842 A, B	CFREG 2.8970 B, C	ACCREG 2.9067 C	ACCPAR 3.9006 D
29	Petro Refining	.3262	ACCREV 2.5431 A	CFRW 2.6806 A	CFREG 3.0485 B	ACCREG 3.2884 B, C	ACCPAR 3.4394 C
308	Plastics	.2833	ACCREV 2.6301 A	CFRW 2.8882 A, B	CFREG 2.9207 B	ACCREG 3.0976 B	ACCPAR 3.4634 C
33	Primary Metal	.3262	ACCREV 2.7628 A	CFRW 2.8814 A, B	CFREG 2.9218 A, B,C	ACCREG 3.2075 B, C	ACCPAR 3.2264 C
331	Steel Work	.2908	ACCREV 2.9058 A	ACCREG 2.9229 A	CFREG 2.9272 A	CFRW 2.9893 A, B	ACCPAR 3.2548 B
34	Fabr. Metal	.2205	ACCREG 2.7709 A	ACCREV 2.8959 A, B	CFRW 2.9033 A,B	CFREG 3.0813 B	ACCPAR 3.3485 C
35	Other Comm. Mach.	.2509	ACCREV 2.6786 A	ACCREG 2.8788 A	CFRW 2.8971 A	CFREG 3.1531 B	ACCPAR 3.3923 B
353	Manuf. Mach.	.3443	CFRW 2.7898 A	ACCREV 2.8078 A, B	CFREG 2.9790 A, B, C	ACCREG 3.1351 B, C	ACCPAR 3.2883 C

*The minimum significant difference between mean ranks was calculated using a Bonferonni procedure adapted for rank ANOVAs with large sample sizes. (See Neter et. al., page 1096 for a discussion.)
**Models with the same group letter are not significantly different from each other.

Table 7 (page 4 of 5)
Cash Flow Predictions by Industry

Panel B: Incremental Predictive Ability (scaled by average total assets) (cont.)

SIC		Min. Sign. Diff.*	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**
355	Spec. Ind. Mach.	.3002	CFREG 2.8311 A	CFRW 2.8379 A	ACCREV 2.9269 A	ACCREG 3.0320 A	ACCPAR 3.3721 B
356	Gen. Ind. Mach.	.2933	CFRW 2.6601 A	ACCREV 2.8083 A, B	CFREG 3.0479 B, C	ACCREG 3.1917 C	ACCPAR 3.2919 C
357	Computer Equip.	.1772	ACCREV 2.8628 A	CFRW 2.9057 A	CFREG 2.9594 A	ACCREG 2.9936 A	ACCPAR 3.2784 B
36	Electr. Equip.	.1905	ACCREV 2.8116 A	ACCREG 2.9651 A	CFRW 2.9752 A	CFREG 2.9862 A	ACCPAR 3.2620 B
366	Communication. Eq.	.1924	CFREG 2.8707 A	ACCREG 2.8978 A	ACCREV 2.9128 A	CFRW 2.9944 A	ACCPAR 3.3243 C
367	Electronics	.1644	ACCREV 2.7336 A	CFRW 2.8637 A, B	ACCREG 2.9795 B, C	CFREG 3.1082 C	ACCPAR 3.3151 D
37	Trans. Equip.	.2982	CFRW 2.7590 A	ACCREV 2.7635 A	ACCREG 3.0270 A	CFREG 3.0338 A	ACCPAR 3.4167 B
371	Motor Vehicles	.2472	ACCREV 2.6974 A	CFRW 2.8738 A	ACCREG 2.9087 A	CFREG 3.2152 B	ACCPAR 3.3050 B
38	Meas. Instr.	.3174	ACCREV 2.6556 A	CFRW 2.8010 A, B	CFREG 3.0128 B, C	ACCREG 3.1888 C, D	ACCPAR 3.3418 D
382	Lab Instruments	.2015	ACCREV 2.7783 A	ACCREG 2.7942 A	CFRW 2.9079 A, B	CFREG 3.0216 B	ACCPAR 3.4979 C
384	Medical Instr.	.1878	ACCREV 2.7598 A	ACCREG 2.8393 A, B	CFRW 2.8509 A, B	CFREG 2.9973 B	ACCPAR 3.5527 C
39	Misc. Manuf.	.2729	ACCREV 2.7698 A	CFRW 2.9302 A	ACCREG 2.9491 A	CFREG 2.9528 A	ACCPAR 3.3981 B

*The minimum significant difference between mean ranks was calculated using a Bonferonni procedure adapted for rank ANOVAs with large sample sizes. (See Neter et. al., page 1096 for a discussion.)
**Models with the same group letter are not significantly different from each other.

Table 7 (page 5 of 5)
Cash Flow Predictions by Industry

Panel B: Incremental Predictive Ability (scaled by average total assets) (cont.)

SIC		Min. Sign. Diff.*	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**
50	Wholesale-Durable Gds	.2189	CFREG 2.8835 A	ACCREG 2.8896 A	ACCREV 2.9151 A	CFRW 3.0789 A, B	ACCPAR 3.2330 B
504	Wholesale – Equip.	.3480	ACCREV 2.7960 A	CFREG 2.9325 A, B	CFRW 2.9954 A, B	ACCPAR 3.0583 A, B	ACCREG 3.2178 B
51	Wholesale-Nondur. Gds.	.2674	ACCREV 2.8080 A	CFRW 2.8623 A, B	ACCREG 3.0725 A, B, C	ACCPAR 3.1196 B, C	CFREG 3.1377 C
541	Grocery Stores	.3070	CFRW 2.6181 A	ACCREV 2.7566 A	CFREG 2.7589 A	ACCREG 2.8210 A	ACCPAR 4.0453 B
59	Misc. Retail	.2231	ACCREG 2.7163 A	CFRW 2.7377 A	ACCREV 2.8436 A	CFREG 2.9067 A	ACCPAR 3.7957 B

*The minimum significant difference between mean ranks was calculated using a Bonferonni procedure adapted for rank ANOVAs with large sample sizes. (See Neter et. al., page 1096 for a discussion.)
**Models with the same group letter are not significantly different from each other.

Table 8
Alternative Industry Groupings

Group #	Group Name	SIC Codes Included	Min Firms per Year*
1	Construction	1500 – 1799	23
2	Food and Tobacco	2000 – 2199	79
3	Textiles and Apparel	2200 – 2399	44
4	Wood Products, Furniture, and Fixtures	2400 – 2599	37
5	Paper Products	2600 – 2699	34
6	Printing and Publishing	2700 – 2799	36
7	Chemicals, Petro, Rubber, and Misc. Plastics	2800 – 3099	203
8	Metal Industries	3300 – 3499	90
9	Industrial, Commercial Machinery & Computers	3500 – 3599	211
10	Electrical Equipment	3600 – 3699	220
11	Transportation Equipment	3700 – 3799	68
12	Measurement Instruments, Photo, & Watches	3800 – 3899	152
13	Misc. Manufacturing Industries	3100 – 3299, 3900 – 3999	70
14	Durable Goods – Wholesale	5000 – 5099	76
15	Non-durable Goods – Wholesale	5100 – 5199	36
16	Food Retailers	5400 – 5499	21
17	Retailers other than Food	5200 – 5399, 5500 – 5799, 5900 – 5999	127

*The final column represents the lowest number of firms from each group in any sample year.

Table 9
Cash Flow Predictions using
Alternative Industry Groupings and
Pooling Observations from the Prior Three Years

Panel A: Absolute Out-of-Sample Forecast Errors

	Cash Flow Forecast Error Scaled by AvgTA		Cash Flow Forecast Error Scaled by Absolute Cash Flow*	
Model	**Mean**	**Median**	**Mean**	**Median**
CFRW^{A}	.0825	.0518	.5757	.5472
CFREG	.0830	.0558	.6043	.5978
ACCREV^{A}	.0811	.0509	.5672	.5310
ACCREG	.0771	.0494	.5601	.5124

*Cash flow forecast errors scaled by absolute cash flow from operations are windsorized at 1. Observations where cash flow from operations equals zero are omitted from the mean and median calculation.

Table 10
ANOVA on Absolute Forecast Errors
estimated within Alternative Industries while pooling
three years observations

Panel A: Significance of Models in Explaining Rank of Forecast Error within Firm-years.

	F-Test	Friedman χ^2
Statistic	204.93	609.15
p-value	(<.01)	(<.01)

Panel B: Bonferonni Pairwise Comparisons of Models

Min. Significant Difference	**.0324***	
Model	**Mean Rank across Firm-Years**	**Grouping****
ACCREG	2.3622	A
ACCREV	2.4480	B
CFRW	2.5385	C
CFREG	2.6513	D

A rank ANOVA was performed by first ranking the forecast errors generated by each model within each firm year. The smallest absolute forecast error was given rank 1 and the largest absolute forecast error was given rank 5. The ANOVA was then run as a complete block design where each block consisted of exactly one firm-year treated under each of the five forecast models. (See Neter et. al., page 1094 for a discussion of this methodology.)

*The minimum significant difference between mean ranks was calculated using a Bonferonni procedure adapted for rank ANOVAs with large sample sizes. (See Neter et. al., page 1096 for a discussion.)

**Models with the same group letter are not significantly different from each other.
[A]While CFRW and ACCREV are estimated for this table using the same procedures as used in table 3, the errors reported are different between the two tables due to differences in samples. This table includes 3,505 firm-years not included in the original analysis due to the original industry grouping rules. This also table excludes forecast errors from 1991 and 1992 included in the original analysis since forecasts for these years cannot be made with CFREG and ACCREG under the three-year pooling method.

Table 11 (page 1 of 2)
Effect of Firm Characteristics on Prediction Models
using Alternative Industry Grouping and Pooling Observations from the Prior Three Years

Panel A: Spearman correlation between median firm-specific absolute forecast errors (scaled by AvgTA) and firm characteristics

		IRVOL		EARNVOL		SALESVOL		AVGTA
CFRW	?	.3544 (<.01)	+	.4958 [<.01]	+	.3193 [<.01]	-	-.4738 [<.01]
CFREG	?	.2326 (<.01)	+	.4400 [<.01]	+	.2737 [<.01]	-	-.3848 [<.01]
ACCREV	+	.3660 [<.01]	+	.5224 [<.01]	+	.3286 [<.01]	-	-.4459 [<.01]
ACCREG	+	.2948 [<.01]	+	.4873 [<.01]	+	.3032 [<.01]	-	-.4248 [<.01]

Predicted signs are given to the left of the correlation coefficient. Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. IRVOL is the firm-specific standard deviation of Inventory divided by one-period-ahead sales. EARNVOL is the firm-specific standard deviation of earnings scaled by average total assets. SALESVOL is the firm-specific standard deviation of sales scaled by average total assts. AVGTA is average total assets.

Table 11 (page 2 of 2)
Effect of Firm Characteristics on Prediction Models
using Alternative Industry Grouping and Pooling Observations from the Prior Three Years

Panel B: Spearman correlation between median firm-specific incremental predictive abilities (scaled by AvgTA) and firm characteristics

	IRVOL		EARNVOL		SALESVOL		AVGTA	
CFRW less CFREG	?	.3148 (<.01)	?	.2234 (<.01)	?	.1696 (<.01)	?	-.2760 (<.01)
CFRW less ACCREV	?	.0221 (<.01)	?	.0328 (<.01)	?	.0335 (<.01)	?	-.0581 (<.01)
CFRW less ACCREG	-	.1312 [>.99]	?	.1078 (<.01)	?	.1134 (<.01)	-	-.1419 [<.01]
CFREG less ACCREV	?	-.2259 (<.01)	?	-.1341 (<.01)	?	-.1045 (<.01)	?	.1308 (<.01)
CFREG less ACCREG	-	-.1420 [<.01]	?	-.0656 (<.01)	?	-.0435 (<.01)	+	.0673 [<.01]
ACCREV less ACCREG	?	.1672 (<.01)	?	.1277 (<.01)	?	.1045 (<.01)	+	-.1071 (.01)

Predicted signs are given to the left of the correlation coefficient. Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. IRVOL is the firm-specific standard deviation of Inventory divided by one-period-ahead sales. EARNVOL is the firm-specific standard deviation of earnings scaled by average total assets. SALESVOL is the firm-specific standard deviation of sales scaled by average total assts. AVGTA is average total assets.

Table 12 (page 1 of 3)
Cash Flow Predictions by Industry using Alternative Industry Groupings and Pooling Observations from the Prior Three Years

Panel A: Absolute Cash Flow Forecast Errors (scaled by average total assets)

		CFRW		CFREG		ACCREV		ACCREG	
#	Industry	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	Construction	.1032	.0686	.0974	.0675	.0962	.0622	.0972	.0593
2	Food and Tobacco	.0749	.0376	.1006	.0630	.0732	.0373	.0964	.0552
3	Textiles and Apparel	.0868	.0549	.0867	.0609	.0800	.0512	.0767	.0517
4	Wood Products, etc.	.0619	.0388	.0620	.0417	.0610	.0388	.0575	.0375
5	Paper Products	.0479	.0324	.0496	.0346	.0471	.0306	.0485	.0344
6	Printing & Publishing	.0569	.0370	.0586	.0402	.0567	.0350	.0549	.0352
7	Chemicals, etc.	.0683	.0423	.0699	.0460	.0667	.0392	.0646	.0407
8	Metal Industries	.0605	.0444	.0594	.0447	.0595	.0418	.0522	.0397
9	Industrial Machinery	.0953	.0602	.0943	.0628	.0956	.0600	.0878	.0555
10	Electrical Equipment	.1025	.0676	.1004	.0687	.1002	.0656	.0954	.0645
11	Transp. Equipment	.0680	.0458	.0700	.0496	.0632	.0427	.0609	.0415
12	Meas. Instr., etc.	.0916	.0603	.0898	.0620	.0879	.0578	.0833	.0547
13	Misc. Manuf. Ind.	.0866	.0580	.0872	.0650	.0835	.0565	.0799	.0579
14	Durable Gds. Whls.	.0935	.0661	.0832	.0654	.0918	.0604	.0807	.0572
15	ND Goods Whls.	.0977	.0611	.1012	.0631	.0957	.0582	.0991	.0622
16	Food Retailers	.0400	.0280	.0400	.0286	.0405	.0298	.0367	.0239
17	Other Retailers	.0798	.0521	.0798	.0584	.0852	.0565	.0701	.0469

Table 12 (page 2 of 3)
Cash Flow Predictions by Industry using Alternative Industry Groupings and Pooling Observations from Prior Three Years

Panel B: Incremental Predictive Ability

	Industry	Min. Sign. Diff.*	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**
1	Construct-ion	.2850	ACCREV 2.3246 A	ACCREG 2.5088 A	CFREG 2.5825 A	CFRW 2.5842 A
2	Food and Tobacco	.1483	ACCREV 2.2196 A	CFRW 2.3175 A	ACCREG 2.6074 B	CFREG 2.8556 C
3	Textiles and Apparel	.1799	ACCREG 2.3301 A	ACCREV 2.3818 A	CFRW 2.6070 B	CFREG 2.6811 B
4	Wood Prod. Furniture, etc.	.1991	ACCREG 2.4041 A	ACCREV 2.4409 A	CFRW 2.5146 A, B	CFREG 2.6404 B
5	Paper Products	.2184	ACCREV 2.3010 A	CFRW 2.4619 A	ACCREG 2.4969 A	CFREG 2.7402 B
6	Printing and Publishing	.2033	ACCREV 2.3714 A	ACCREG 2.4304 A	CFRW 2.4786 A	CFREG 2.7196 B
7	Chemicals, Petro, Rubber, etc.	.0909	ACCREG 2.3756 A	ACCREV 2.4001 A	CFRW 2.5034 B	CFREG 2.7209 C
8	Metal Industries	.1279	ACCREG 2.2843 A	ACCREV 2.4929 B	CFREG 2.6047 B	CFRW 2.6181 B
9	Industrial, Comm. Mach. etc.	.0912	ACCREG 2.3277 A	ACCREV 2.4952 B	CFRW 2.5379 B	CFREG 2.6392 C

*The minimum significant difference between mean ranks was calculated using a Bonferonni procedure adapted for rank ANOVAs with large sample sizes. (See Neter et. al., page 1096 for a discussion.)
**Models with the same group letter are not significantly different from each other.

Table 12 (page 3 of 3)
Cash Flow Predictions by Industry using Alternative Estimation Procedures

Panel B: Incremental Predictive Ability (cont.)

	Industry	Min. Sign. Diff.*	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**	Model Mean Rank Group**
10	Electrical Equipment	.0828	ACCREG 2.3573 A	ACCREV 2.4747 B	CFREG 2.5689 C	CFRW 2.5992 C
11	Transport. Equipment	.1551	ACCREG 2.3274 A	ACCREV 2.4168 A, B	CFRW 2.4958 B	CFREG 2.7599 C
12	Measurement Instr., Photo & Watches	.0995	ACCREG 2.3296 A	ACCREV 2.4598 B	CFRW 2.5812 C	CFREG 2.6293 C
13	Misc. Manuf. Industries	.1540	ACCREG 2.3689 A	ACCREV 2.3945 A, B	CFRW 2.5430 B, C	CFREG 2.6937 C
14	Durable Goods – Wholesale	.1492	ACCREG 2.3773 A	ACCREV 2.4697 A, B	CFREG 2.5313 B, C	CFRW 2.6218 C
15	Non-durable Goods – Wholesale	.2090	ACCREV 2.4302 A	ACCREG 2.4679 A	CFRW 2.5019 A	CFREG 2.6000 A
16	Food Retailers	.2564	ACCREG 2.3097 A	CFREG 2.5199 A, B	CFRW 2.5710 B	ACCREV 2.5994 B
17	Retailers other than Food	.1138	ACCREG 2.2669 A	CFRW 2.4801 B	ACCREV 2.6044 C	CFREG 2.6486 C

*The minimum significant difference between mean ranks was calculated using a Bonferonni procedure adapted for rank ANOVAs with large sample sizes. (See Neter et. al., page 1096 for a discussion.)
**Models with the same group letter are not significantly different from each other.

Table 13
Model Parameters of food retailers
versus non-durable goods wholesalers.

Variable	Non-durable goods wholesale	Food retail	Difference
Mean (α_i)	.1160	.0210	.0950**
Mean (β_i)	.1178	.0902	.0275**
Mean (γ_i)	.1939	.1041	.0898**
Mean (π_i)	.2284	.2598	-.0310
Mean (λ_i)	.1846	.2046	-.0200
Cross-sectional variation in mean firm-specific parameters			
Std Dev (α_i)	.0748	.0203	.0545**
Std Dev (β_i)	.0685	.0323	.0362**
Std Dev (γ_i)	.2721	.0415	.2306**
Std Dev(π_i)	.1982	.0679	.1303**
Std Dev(λ_i)	.1843	.0605	.1235**
Time-series variation in mean annual parameters			
Std Dev (α_t)	.0081	.0041	.0040*
Std Dev (β_t)	.0075	.0053	.0022
Std Dev (γ_t)	.0704	.0080	.0624**
Std Dev(π_t)	.0318	.0162	.0156*
Std Dev(λ_t)	.0271	.0151	.0219*

*Significant at greater than a 5% level. **Significant at greater than a 1% level. Significance tests for standard deviations were performed using an F-test on the respective variances. All other significance tests were performed using a t-test.

Means reported for the parameters (α_i, β_i, γ_i, π_i, and λ_i) are the mean firm-specific parameters within the industry. Cross-sectional standard deviations are the standard deviations of the firm-specific parameters across all firms in the industry (i.e. mean alpha is calculated for each firm and then the standard deviation of firm alphas is calculated.) Time-series standard deviations are the standard deviation of annual mean parameters (i.e. mean alpha is calculated for each year and then the standard deviation of annual alphas is calculated.)

α is the ratio of ending accounts receivable to annual sales. β is the ratio of accounts payable to annual inventory purchases plus operating expenses. γ is the fraction of next period's cost of goods sold included in ending inventory. π is the gross profit percentage. λ is the ratio of operating expenses to sales.

Table 14 (page 1 of 2)
The Incremental Cash Flow Information
Contained in Actual Future Sales

Panel A: Prediction Models Incorporating Actual Future Sales

Cash flow-based regression model – actual sales (CFREG*):

$$E(CFO_{i,t+1}) = \theta_0 + \theta_1 CFO_{i,t} + \theta_2 S_{i,t+1} + \theta_3 \Delta S_{i,t+2}$$

Accrual-based regression model – actual sales (ACCREG*):

$$E(CFO_{i,t+1}) = \theta_0 + \theta_1 CFO_{i,t} + \theta_2 \Delta AR_{i,t} + \theta_3 \Delta AP_{i,t} + \theta_4 \Delta AccExp_{i,t} - \theta_5 \Delta AccIT_{i,t} + \theta_6 \Delta INV_{i,t} + \theta_7 S_{i,t+1} + \theta_8 S_{i,t} + \theta_9 \Delta S_{i,t+2}$$

Panel B: Estimated Coefficients (Dependent Variable is CFO at time t.)

Variable	CFREG*			ACCREG*		
	Pred.	Coefficient	t-statistic	Pred.	Coefficient	t-statistic
Intercept	?	-.4360	-8.02	?	-.3284	-7.66
CFO_{t-1}	+	.5184	40.32	+	.6511	46.66
ΔAR_{t-1}				+	.3946	18.90
ΔINV_{t-1}				+	.2707	13.27
ΔAP_{t-1}				-	-.4509	-18.96
$\Delta AccExp_{t-1}$				-	-.3783	-12.43
ΔITP_{t-1}				-	-.7473	-13.16
S_t	+	.0285	26.98	+	.0359	9.23
S_{t-1}				-	-.0172	-4.58
ΔS_{t+1}	?	.0123	3.82	-	.0077	3.30

The θ parameters in models CFREG and ACCREG are estimated with weighted least squares regressions (weighted by average total assets) within the alternative industry groupings listed in table 8. Years t through t-2 for each industry are pooled and the coefficients estimated by regressing current year cash flows on prior year cash flow and accruals. CFO is cash flow from operations. ΔAR is change in accounts receivable (net). ΔAP is change in accounts payable. ΔAccExp is change in accrued expense. ΔAccIT is change in accrued income tax. ΔInv is change in inventory. Inv is the level of ending inventory. S_t is actual sales in period t. ΔS_{t+2} is the actual change in sales from period t+1 to period t+2.

Table 14 (page 2 of 2)
The Incremental Cash Flow Information Contained in Actual Future Sales

Panel C: Effect of Actual Sales on Absolute Cash Flow Errors

	Cash Flow Forecast Error (scaled by AvgTA)		Cash Flow Forecast Error (scaled by Absolute Cash Flow)	
Model	**Mean**	**Median**	**Mean[2]**	**Median**
CFREG[1]	.0829	.0560	.6012	.5908
CFREG*	.0767	.0499	.5581	.5107
Effect of Actual Sales on CFREG (CFREG-CFREG*)	.0062 *19.86* [<.01]	.0058 [<.01]	.0431 *22.79* [<.01]	.0494 [<.01]
ACCREG[1]	.0768	.0492	.5561	.5046
ACCREG*	.0753	.0483	.5497	.4922
Effect of Actual Sales on ACCREG (ACCREG-ACCREG*)	.0015 *4.84* [<.01]	.0007 [<.01]	.0064 *4.82* [<.01]	.0071 [<.01]
Differential Effect of Actual Sales on CFREG versus ACCREG	.0047 *15.10* [<.01]	.0047 [<.01]	.0367 *17.31* [<.01]	.04041 [<.01]

The top number in each cell is the absolute forecast error (or difference in absolute forecast errors) generated by each model. Numbers in italics are t-statistics. One-tailed p-values are shown in brackets. P-values for means are calculated using a paired t-test while p-values for medians are calculated using a non-parametric sign test.

[1]The cash flow forecast errors generated by CFREG and ACCREG differ from the mean and median errors reported in table 9 due to the omission of 3,426 firm-years from the current table due to the lack of information for sales in period t+1 and/or t+2.

[2]Forecast errors scaled by absolute cash flow from operations are windsorized at one when calculating the mean forecast error.

Panel D: Spearman Correlation between the Effect of Sales Estimation Error and Firm Characteristics

	IRVOL		EARNVOL		SALESVOL		AVGTA	
ACCREG less ACCREG*	+	.0315 [.06]	?	.0551 (.01)	?	-.0126 (.54)	?	-.0156 (.37)

Predicted signs are given to the left of the correlation coefficient. Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. IRVOL is the firm-specific standard deviation of Inventory divided by one-period-ahead sales. EARNVOL is the firm-specific standard deviation of earnings scaled by average total assets. SALESVOL is the firm-specific standard deviation of sales scaled by average total assts. AVGTA is average total assets.

Table 15 (page 1 of 2)
Effect of Actual Sales on Forecast Errors (scaled by AvgTA) by Industry

		CFREG less CFREG*		ACCREG less ACCREG*		Difference	
		Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
1	Construction	.0064 2.20 [.02]	.0032 [.06]	.0074 *2.32* [.02]	.0006 [.38]	-.0010 -.29 [.62]	.0035 [.11]
2	Food and Tobacco	.0252 9.21 [<.01]	.0092 [<.01]	.0201 *6.91* [<.01]	.0021 [<.01]	.0051 2.01 [.03]	.0047 [<.01]
3	Textiles and Apparel	.0070 4.32 [<.01]	.0088 [<.01]	.0008 *.68* [.25]	.0005 [.33]	.0062 3.07 [<.01]	.0074 [<.01]
4	Wood Products, etc.	.0039 2.23 [.02]	.0024 [.09]	-.0007 *-.63* [.74]	.0005 [.18]	.0047 2.67 [.01]	.0015 [.04]
5	Paper Products	.0066 3.77 [<.01]	.0057 [<.01]	.0030 *1.97* [.03]	.0019 [<.01]	.0036 2.17 [.02]	.0013 [.23]
6	Printing & Publishing	.0048 4.23 [<.01]	.0036 [<.01]	.0008 *.87* [.20]	.0014 [.03]	.0040 3.02 [<.01]	.0047 [<.01]
7	Chemicals, etc.	.0045 6.15 [<.01]	.0041 [<.01]	.0017 *2.97* [<.01]	.0008 [<.01]	.0028 4.09 [<.01]	.0034 [<.01]
8	Metal Industries	.0064 6.96 [<.01]	.0077 [<.01]	.0003 *.62* [.27]	.0005 [.02]	.0061 6.93 [<.01]	.0058 [<.01]
9	Industrial Machinery	.0041 3.99 [<.01]	.0057 [<.01]	-.0011 *-.84* [.80]	.0005 [.10]	.0053 5.31 [<.01]	.0060 [<.01]
10	Electrical Equipment	.0061 7.77 [<.01]	.0062 [<.01]	.0023 *2.85* [<.01]	.0016 [<.01]	.0039 4.34 [<.01]	.0034 [<.01]

The top number in each cell is the absolute forecast error (or difference in absolute forecast errors) generated by each model. Numbers in italics are t-statistics. One-tailed p-values are shown in brackets. P-values for means are calculated using a paired t-test while p-values for medians are calculated using a non-parametric sign test.

Table 15 (page 2 of 2)
The Incremental Cash Information Contained in
Actual Future Sales by Industry

		CFREG less CFREG*		ACCREG less ACCREG*		Difference	
		Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
11	Transp. Equipment	.0078 5.90 [<.01]	.0063 [<.01]	.0003 *.36* [.37]	.0008 [.07]	.0075 5.54 [<.01]	.0060 [<.01]
12	Meas. Instr., etc.	.0053 6.89 [<.01]	.0077 [<.01]	.0004 *.74* [.26]	.0009 [<.01]	.0049 7.19 [<.01]	.0059 [<.01]
13	Misc. Manuf. Ind.	.0035 3.63 [<.01]	.0055 [<.01]	-.0011 *-1.40* [.92]	-.0010 [>.99]	.0046 3.94 [<.01]	.0059 [<.01]
14	Durable Gds. Whls.	.0013 1.38 [.09]	.0047 [<.01]	-.0019 *-1.55* [.94]	.0004 [.33]	.0032 2.40 [<.01]	.0032 [<.01]
15	ND Goods Whls.	.0023 .77 [.23]	.0040 [<.01]	-.0003 *-.18* [.58]	.0002 [.41]	.0027 .91 [.19]	.0040 [<.01]
16	Food Retailers	.0032 2.46 [<.01]	.0014 [.18]	.0001 *.07* [.48]	-.0002 [.68]	.0031 2.28 [.02]	.0011 [.18]
17	Other Retailers	.0079 7.41 [<.01]	.0080 [<.01]	-.0004 *-.53* [.71]	.0001 [.34]	.0083 8.13 [<.01]	.0077 [<.01]

The top number in each cell is the absolute forecast error (or difference in absolute forecast errors) generated by each model. Numbers in italics are t-statistics. One-tailed p-values are shown in brackets. P-values for means are calculated using a paired t-test while p-values for medians are calculated using a non-parametric sign test.

Timothy R. Yoder
Certified Public Accountant

Curriculum Vitae

Education

Spring 2001 – Current	The Pennsylvania State University Smeal College of Business Ph.D. Candidate in Accounting Expected Graduation: August 2006
Fall 1990 - Spring 1994	University of Colorado at Colorado Springs College of Business Bachelor of Science in Accounting, May 1994 Graduated with Honors: Magna Cum Laude

Professional Experience

June 1994 - Dec 2000	BKD, LLP (Formerly Baird, Kurtz & Dobson, CPAs) Colorado Springs, CO Tax Supervisor

Working Papers

The Incremental Cash Flow Predictive Ability of Accrual Models. (Dissertation)

What Do Analysts Really Predict? Inferences from Earnings Restatements and Managed Earnings. (with Dan Givoly and Carla Hayn)

Teaching Experience

The Pennsylvania State University
Principles of Taxation (Summers 2002 through 2005)
Principles of Accounting (Summer 2001)

Honors and Awards

Smeal College General Scholarship, Spring 2001

Graduate School Enhancement Funds, Fall 2001 through Spring 2004

Jane O. Burns Scholarship, Fall 2001 and Spring 2002

J. Kenneth and Nancy Jones Scholarship, Fall 2002 through Spring 2004.