The Incremental Cash Flow Predictive Ability of Accrual Models[*]

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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 and using direct observations on the new model's parameters rather than their OLS estimation. The Barth, Cram, and Nelson model is further modified to allow the incorporation of accrual-based prediction of future sales. The evidence shows that the incremental predictive ability of accrual models is not uniform across firms. The paper also investigates the factors that affect the cross-sectional variability in the incremental predictive ability of accrual models. Specifically, the incremental predictive ability of the accrual model is found to be decreasing in the volatility of earnings and sales as well as decreasing in the volatility of the ratio of inventory to future sales. The evidence does not support the hypotheses that the incremental predictive ability is increasing in size.

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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, it further develops the estimation and specification of the accrual-based prediction model presented in prior literature. Specifically, it builds upon the model of Barth, Cram and Nelson (2001) to incorporate the cash flow implications of growth in future sales and allows management to impound their forecasts of future sales into ending inventory. The paper assesses the role of inventory accruals in predicting future sales and hence future cash flows and the extent to which this type of accrual contributes to the incremental predictive ability of accrual-based models. The paper further uses alternative, firm-specific, estimates of the parameters of the accrual-based prediction models. Finally, in recognition of the possibility that accruals may be more informative for some firms than others, 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.

The main finding of the paper is that while, on average, a positive incremental predictive power of accrual-based models over cash-flow-only models cannot be detected, their incremental predictive power varies considerably depending on firm characteristics. In particular, the accrual-based model (when estimated with WLS) possesses more incremental predictive power with respect to future cash flows for firms with lower volatility of earnings, lower volatility of sales, and lower volatility of the ratio of inventory to future sales. While the incremental predictive ability varies with firm characteristics, the paper fails to find evidence that the accrual model for firms in the extreme deciles of each firm characteristic contains positive incremental predictive ability.

A secondary contribution of this paper is the finding that a random walk model of cash flows produces lower out-of-sample forecast errors than a model regressing current cash flows on prior cash flows. This is an important finding since identifying the appropriate benchmark model is essential to measuring the incremental predictive ability of accrual-based models. Kim and Kross (2005) would have likely reached a different conclusion regarding the incremental predictive ability of earnings had they used a random walk model of cash flows as their benchmark.

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 of the relationship between firm characteristics and predictive ability. Section 4 discusses the sample selection. Section 5 provides empirical results and section 6 concludes and offers avenues for future research.

2. Literature Review

Three research methods 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 all 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 value relevance approach to evaluating the usefulness of accruals has two shortcomings. First, as discussed by Holthhausen and Watts (2001), it is not the FASB's intent to produce earnings that reflect the change in a firm's market value of equity.[3] Second, value relevance studies rely upon two assumptions: market efficiency and adequate control for risk. 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.

[3] In fact, FASB SFAC number 1, paragraph 41, states " . . .financial accounting is not designed to measure directly the value of an enterprise".

Another method 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. The conclusion of an association is based on significant coefficients and/or an increase in adjusted r-squared. Kim and Kross (2005) show that while the value relevance of earnings has decreased over time, the association between earnings and one-period ahead cash flow has increased over time.[4] Dechow and Dichev (2002) approach the association in a similar but slightly different manner. They show that past, present, and future cash flows "map into" accruals by regressing accruals in period t on cash flows in period t-1, period t, and period t+1.

An association between accruals in period t and cash flows in period t+1 does *not* imply that accruals in period t can be used to *predict* (out-of-sample) cash flows in period t+1. Association studies estimate the association between cash flows and lagged accruals within years. Association studies find that for a given year, accruals are associated with future cash flows. However, this association may vary considerably from year to year. Out-of-sample forecasting (as done in this paper) requires both an association between accruals and future cash flows and the ex-ante ability to estimate this association for the year being forecast. An ex-ante prediction of the association between accruals and future cash flows is difficult if the association is volatile over time.

[4] 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 method to assess the usefulness of accruals measures 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, the Kim and Kross (2005) study uses a regression of current cash flows on prior cash flows as their cash flow benchmark model. This study shows that a random walk model of cash flows produces smaller out-of-sample forecast errors than the regression model used by Kim and Kross (2005) 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 aggregate earnings. This suggests that models using disaggregated accruals *may* have incremental predictive ability over cash-flow-based models, even if models using aggregate earnings do not.

This study investigates the incremental predictive ability of models using disaggregated accruals versus aggregate earnings. 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.

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 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, inventory changes are likely based, in part, on management's expectation of future sales. In this study, I extend the BCN model by allowing sales growth and inventory decisions based on management expectation of future sales.

In line with the BCN model, I make the following assumptions regarding earnings, sales, accounts receivable, and accounts payable:

$GP_t = \pi S_t$
$OPEX_t = \lambda S_t$
$EARN_t = (\pi-\lambda)S_t$
$S_t = S_{t-1} + G_t$
$AR_t = \alpha S_t$
$AP_t = \beta(PURCH_t+OPEX_t)$

where

π = Gross profit percentage,
α = Fraction of annual sales uncollected at year-end,
β = Fraction of annual inventory purchases and operating expenses unpaid at year-end,

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.
π, α, β and λ are assumed to be constant over time.

Unlike BCN, I do *not* assume $E_t[G_{t+1}] = 0$. In addition, 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. That is:

$$INV_t = \gamma(1-\pi)(S_t + E_t[G_{t+1}]) \quad (1)$$

where INV_t is inventory at the end of period t. As a result, the level of ending inventory is interpreted as management's sales projections. 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 expected cost of goods sold (COGS) plus expected operating expenses plus expected change in inventory less expected change in accounts payable:

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

I derive each component of expected cash payments separately. 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:

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

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 component of expected cash payments (the second term in equation 3) is the expected change in inventory for period t+1. The expected change in inventory in period t + 1 is a function of 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:

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

Noting that purchases equal COGS plus the change in inventory:

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

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

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

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

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

The expected change in operating expenses can be derived:

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

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

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

Finally, total expected cash payments is calculated as equation 5 plus equation 6 less equation 10:

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

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

Net Expected Cash Flows

Net expected cash flows is now derived as 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 used to test 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, CFRW, 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):

$$E\left(CFO_{i,t+1}\right) = CFO_{i,t} \tag{15}$$

where

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

The second cash-flow-based prediction model, CFREG, predicts next period's cash flows as a linear function of current cash flows. The following regression is estimated on a cross-section of firms within industry and year:[5]

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

Cash Flow Regression Model (Model CFREG):

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

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

3.2.2 Accrual-based prediction models

I separate accounts payable included in the analytical model (equation 14) into accounts payable, accrued expenses (AccExp), and accrued 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):

$$\begin{aligned} E\left(CFO_{i,t+1}\right) &= CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t} + (1-\beta)\Delta INV_{i,t} \\ &+ \left[\frac{(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]}{\gamma(1-\pi)}\right] INV_{i,t} - [(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]]S_{i,t} \\ &- (1-\beta)\gamma(1-\pi)E\Delta Sales2_{i,t} \end{aligned} \tag{17}$$

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,[6]
$\Delta AP_{i,t}$ =	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.

[6] 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.

ACCPAR requires a proxy for management's 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 year t growth rate (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. Tests (not reported) show that g is highly correlated with analysts' forecasts of one-year-ahead growth in sales.

Estimation of the model requires estimates of the parameters α, β, γ, π, and λ. For ACCPAR, firm-specific estimates of these parameters are derived as the average parameter for each firm over the current and prior two years.

In contrast to ACCPAR, ACCREG estimates the coefficients using a weighted least squares regression. The coefficients on CFO and ΔAR (ΔAP, ΔAccExp, and ΔAccIT) are restricted in the WLS estimation to their theoretical values in the analytical model of 1 (–1).[7]

Accruals Regression Model (Model ACCREG):

$$E\left(CFO_{i,t+1}\right)=\theta_0+CFO_{i,t}+\Delta AR_{i,t}-\Delta AP_{i,t}-\Delta AccExp_{i,t}-\Delta AccIT_{i,t}+ \theta_1\Delta INV_{i,t}+\theta_2 INV_{i,t}+\theta_3 S_{i,t}+\theta_4 E\Delta Sales2_{i,t} \quad (18)$$

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

[7] Sensitivity analyses were performed allowing the coefficients on CFO, ΔAR, ΔAP, ΔAccExp, and ΔAccIT to be determined by the WLS regression versus being restricted to one or negative one. For the cross-sectional sample of firms, the restricted regression produced slightly (but insignificantly) lower absolute forecast errors than the unrestricted regression. For the time-series sample of firms, the restricted regression produced significantly lower absolute forecast errors than the unrestricted regression.

the model parameters capture the entire relationship between current accruals and future cash flows.

The predictive ability of the cash-flow-based models (CFRW and CFREG) and the accrual-based models (ACCPAR and ACCREG) is gauged by their absolute forecast errors. In assessing the incremental predictive ability of each accrual-based model, the prediction errors produced by each accrual-based model will be compared to the prediction error produced by the more accurate cash-flow-based model.

3.2.3. Empirical models using actual future sales

As discussed at the end of section 3.1, one factor that will decrease the power of the accrual model is the prediction error when using ending inventory to predict future sales (henceforth, sales estimation error[8]). I modify ACCPAR and ACCREG by substituting actual sales in t+1 for INV/γ(1-π) and the actual change in sales from t+1 to t+2 for EΔSales2.[9] Actual sales in period t+1 and t+2 are also added to the CFREG model to allow the benchmark model the same exogenous information as the accrual models. CFRW, being a pure random walk, is not modified. The modified models are denoted below as CFREG*, ACCPAR* and ACCREG*, respectively:

*Model CFREG**

$$E\left(CFO_{i,t+1}\right) = \theta_0 + \theta_1 CFO_{i,t} + \theta_2 S_{t+1} + \theta_3 S_{t+2} + \varepsilon_{i,t} \quad (19)$$

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[8] "Sales estimation error" results, in part, from management's inability to accurately forecast future sales. However, it also results from management inability or unwillingness to determine ending inventory solely by reference to future sales.

[9] The difference in predictive ability between the models with and without actual sales is a result of both the error with which $INV_t/\gamma(1-\pi)$ predicts S_{t+1} and the error with which $E\Delta Sales2_t$ predicts G_{t+2}. However, the effect of S_{t+1} on CFO_{t+1} likely overwhelms the smaller effect of G_{t+2} on CFO_{t+1}. Future versions of the paper will address these confounding effects.

*Model ACCPAR**

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

By substituting $G_{t+1} = S_{t+1} - S_t$ and $G_{t+2} = E\Delta Sales2_t$, we obtain ACCPAR*:

$$E(CFO_{i,t+1}) = CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t} + (1-\beta)\Delta INV_{i,t} + [(1-\alpha)-(1-\beta)[(1-\pi)+\lambda]]G_{i,t+1} - (1-\beta)\gamma(1-\pi)G_{i,t+2} \quad (20)$$

*Model ACCREG**

As with ACCREG compared to ACCPAR, ACCREG* contains the same variables ACCPAR*, but the coefficients are estimated using a WLS regression versus estimating the individual model parameters. As in equation 18, the coefficients on CFO and ΔAR (ΔAP, ΔAccExp, and ΔAccIT) are restricted in the WLS estimation to their theoretical values in the analytical model of 1 (-1):

$$E(CFO_{i,t+1}) = \theta_0 + CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t} + \theta_1 \Delta INV_{i,t} + \theta_2 G_{t+1} + \theta_3 G_t \quad (21)$$

Comparing the errors produced by ACCPAR* to ACCPAR and ACCREG* to ACCREG will indicate the effect on forecast errors of the error inherent in estimating period t+1 sales through period t ending inventory. I expect ACCPAR* (ACCREG*) to produce significantly lower absolute forecast errors than ACCPAR (ACCREG). I also expect the inclusion in CFREG* of actual future sales to result in a lower forecast error than CFREG. As discussed at the end of section 3.3, future work will determine if the firm-specific level of sales estimation error can be used to identify subsets of firms in which accrual models have incremental predictive ability.

3.3 Firm characteristics affecting the predictive ability of accrual models

This section discusses the relationship between the power of the accrual-based cash flow prediction model and the following firm characteristics: stability of the ratio of inventory to future sales, volatility of sales and earnings, and firm size. [10]

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

The power of inventory to predict future sales depends on the validity of the model assumption that $INV_t=\gamma(1-\pi)Sales_{t+1}$. I test the validity of this assumption for each firm by the extent of the volatility in the ratio of inventory to sales. The more stable the ratio, the more reliable the inventory-based sales forecast. The 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.[11] 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. Hence,

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

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 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 when the volatility of sales and the volatility of earnings are higher. In addition,

[10] 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.

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

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 a positive or negative effect on the ability of the accrual model compared to the cash flow model is an empirical question. Hence, I do not make a prediction as to the direction of the effect:

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 decisions of any one customer.

Firm size is likely 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 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 models ACCPAR and ACCREG over models CFRW and CFREG.

To determine if accrual-based models contain incremental predictive ability for certain subsets of firms, firms are split into deciles based on each of the firm characteristics discussed. The benchmark and accrual models are estimated within the highest (or lowest depending on the characteristic) deciles and the incremental predictive ability of the accrual models determined. It is possible that the accrual model for large firms contains incremental predictive ability, but that incremental predictive ability cannot be detected for firms on average. Conversely, it is also possible that firm size is positively correlated with incremental predictive ability but incremental predictive ability is still negative for all firms.

4. Sample Selection

The main sample consists of firm years from 1989 through 2003 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, the model 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[12]. In addition, firm-years are included only if there is information from the prior two years 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 sample ends in 2003 as 2004 firm-years do not have the following year's cash flow 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).

To perform the analysis of incremental predictive ability for firms in the extreme deciles of each firm characteristic, a sample of firms with data available for each year from 1978 to 2004 is collected (henceforth the time-series sample). A time-series estimation is necessary as there are insufficient observations for each industry within the extreme deciles to perform a cross-sectional estimation. Table 3 describes the data collection process. To eliminate firms that are not inventory-intensive, firms are eliminated that are not in the wholesaling, retailing, or manufacturing industries. Firms

[12] 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 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 ΔAccIT for that observation is set to zero.

are required to have cash flows from operations, change in accounts receivable, change in accounts payable, change in accrued expense, change in inventory, level of ending inventory, positive sales, positive cost of goods sold, and positive selling, general and administrative expense. For years prior to the effective date of SFAS 95 cash flow was estimated using the balance sheet approach. Hribar and Collins (2001) find that mergers, acquisitions, and divestitures produce significant error in estimating cash flows from operations when using the balance sheet approach. Firms experiencing an increase in total assets of greater than 30% in any year ending prior to July, 1988 (the effective date of SFAS 95) are eliminated as they are likely to have experienced a merger or acquisition. Firms with gain or loss from discontinued operations greater than 30% of the absolute value of earnings before extraordinary items are eliminated as they are likely to have experienced a divesture. This selection criteria results in 192 firms in the time-series sample.

5. Results

5.1. Descriptive statistics

Table 2, panel A presents the distribution of financial statement variables for the main sample. The mean (median) average total assets of firm-years included in the main sample are $1.9 billion ($170 million). The mean (median) sales of sample firm-years are $2.1 billion ($216 million). On average, firms appear to be growing during the sample period as the mean and median changes in all accruals are positive. Table 2, panel B presents the correlations between all financial statement variables (scaled by average total assets). The highest Pearson correlation is between ΔAR and ΔAP at .41.

Table 2, panel C presents the distribution of the model parameters and the firm characteristics. The mean sales uncollected at year-end (α) is 17%. The mean payments to vendors outstanding (β) is 16%. Ending inventory contains an average of 28% of next period sales (γ). The mean gross profit percentage (π) is 36% while operating expenses average 27% of sales (λ). Table 2, panel D presents the correlations between parameters and firm characteristics. Consistent with the hypothesis of this study, SALESVOL and EARNVOL are significantly correlated with all the parameters. However, AVGTA is not significantly correlated with either γ or π.

Table 4, panel A provides the distribution of financial statement variables for the time-series sample. The firms in the time-series sample are larger than the firms in the cross-sectional sample. The mean (median) total assets for the time-series firms are $3.5 billion ($472 million) versus the mean (median) total assets for the cross-sectional sample firms of $1.9 billion ($170 million). Table 4, panel B presents the correlations between all financial statement variables scaled by average total assets. All Pearson and Spearman correlations for the time-series sample are in the same direction as the correlations for the cross-sectional sample.

Table 4, panel C presents the distribution of the model parameters and firm characteristics for the time-series sample. All model parameters are similar to those of the cross-sectional sample. The time-series firms have higher IRVOL and EARNVOL than the firms in the cross-sectional sample. Mean IRVOL and EARNVOL is .048 and .051, respectively, for the time-series sample compared to .055 and .073, respectively, for the cross-sectional sample. SALESVOL for the time-series sample is .292 compared to SALESVOL for the cross-sectional sample of .261. Table 4, panel D presents the correlations between the model parameters and firm characteristics. All significant correlations are in the same direction as the correlations for the cross-sectional sample.

5.2 Cash flow predictions where sales are forecasted using ending inventory.

The coefficients in CFREG and ACCREG are estimated by regressing year t cash flows on year t-1 observations of the independent variables. The coefficients in 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 5, panel A presents the coefficients from estimating the cash flow-based CFREG and the two accrual-based models (ACCPAR and ACCREG). The cash-flow-based CFRW does not require estimation as the coefficient on cash flow is restricted to equal 1. With the exception of the coefficient on $Sales_{t-1}$ in ACCREG, all of the coefficients are significant and in the direction predicted by the model.

Table 5, panel B presents the out-of-sample forecast errors generated by each model. CFRW generates lower absolute forecast errors than CFREG and is therefore used as the benchmark model to measure the incremental predictive ability of ACCPAR and ACCREG. The superiority of ACCREG over ACCPAR suggests that either the parameters derived in the analytical model do not fully capture the relationship between future cash flows and the level of ending inventory and/or the coefficients estimated in ACCREG are more stable over time than the parameters estimated in ACCPAR.

On average, neither ACCPAR nor ACCREG produce significantly lower forecast errors than CFRW. The median (mean) forecast error of CFRW is 4.9% (7.7%) of assets while the median (mean) error of ACCPAR is 7.4% (11.9%) of assets. The median (mean) forecast error of ACCREG is 5.2% (8.0%) of assets. Therefore, I find no evidence that either ACCPAR or ACCREG contains incremental forecast ability over CFRW. Note that the conclusion regarding incremental predictive ability is sensitive to whether CFRW or CFREG is chosen as the cash flow benchmark. ACCREG does produce a significantly lower median forecast error than CFREG. This suggests that the conclusions of the Kim and Kross (2005) study (regarding the incremental predictive ability of earnings-based models over cash-flows-based model) would have likely been different had the benchmark model been a random walk cash flow model rather than a scaled version of CFREG.

Table 6, Panel A provides the correlation between firm characteristics and the absolute forecast errors of each of the four models. As expected, the absolute forecast errors of ACCPAR and ACCREG are increasing (decreasing) in IRVOL, EARNVOL, and SALESVOL (AVGTA). Table 6, panel B provides the correlations between firm characteristics and the *incremental* predictive abilities of the models. As in the analysis of Table 5, since CFRW provides a lower absolute forecast error than CFREG, attention is focused on the incremental predictive ability of ACCPAR and ACCREG over CFRW. Consistent with hypotheses 2 and 3, the incremental predictive ability of ACCREG over CFRW is decreasing in IRVOL, EARNVOL, and SALESVOL. However, the incremental predictive ability of ACCPAR over CFRW is decreasing in EARNVOL only. However, the results do not support hypothesis 4 since no association is detected between AVGTA and the incremental predictive ability of either ACCPAR or ACCREG over CFRW.

Tables 5 and 6 fail to provide evidence that accrual models have on average incremental predictive ability beyond that of cash flow models. However, the predictive ability of accrual models compared to cash flow models is greater for firms that operate in a more stable environment. Section 5.5 presents tests to determine if the accrual models contain positive incremental predictive ability compared to cash-based models for a subset of firms based on firm characteristics.

5.3 Cash flow predictions using actual future sales

Table 7 provides the results from estimating models 3* and 4* and compares their estimation error to those produced by models 1 and 2*. As explained in section 3.2.3, models 2*, 3* and 4* assume perfect foresight of future sales. The analysis of the relative performance of these models allows the separation of the effect of the sales estimation error from other factors affecting the predictive power of accruals.

Table 7, panel b provides the forecast errors from CFRW, CFREG*, ACCPAR* and ACCREG*. CFREG* produces a significantly lower mean forecast error than CFRW and is therefore used as the benchmark for measuring the incremental predictive ability of ACCPAR* and ACCREG*. ACCPAR* produces slightly smaller (but significant) median forecast errors than CFREG*. There is no evidence that ACCPAR* or ACCREG* produce smaller mean forecast errors than CFREG*. ACCPAR* and ACCREG* perform similarly to each other. This indicates that the inferior performance of ACCPAR relative to ACCREG in Table 5 is likely due to inadequate predictions of future sales using $INV/\gamma(1-\pi)$. ACCREG* generates slightly (but significant) lower absolute forecast errors (scaled by average total assets) than ACCPAR*.

The results fail to find either ACCPAR* or ACCREG* produce, on average, lower mean forecast errors than CFREG*. That is, on average, this study is unable to detect an incremental predictive ability of accruals over cash flows even if future sales are known. However, Table 8, panel B shows that the incremental predictive ability of both ACCPAR* and ACCREG* over CFREG* is increasing in AVGTA and decreasing in IRVOL, EARNVOL, and SALESVOL. Therefore, accrual models contain more incremental forecast ability for large firms and stable firms, than for small firms and volatile firms, respectively when future sales are known.

5.4 The effect of sales estimation error

Table 9, panel A compares the forecast errors from tables 5 and 7 to determine the effect of the error when using inventory to predict future sales (sales estimation error) on the performance of the accrual models. The results show that ACCPAR* (ACCREG*) performs better than ACCPAR (ACCREG) which does not use actual sales numbers. Not surprisingly, sales estimation error impounded in ending inventory does significantly affect the predictive ability of both accrual models. Table 9, panel B presents the spearman correlations between the effect of sales estimation error on predictive ability and firm characteristics. Surprisingly, no evidence is found that IRVOL is positively correlated with the effect of sales estimation error in ACCPAR or ACCREG.

5.5 Incremental predictive ability of firms in extreme deciles based on firm characteristics.

Table 10, panel A provides the absolute forecast errors produced by each model for the time-series sample of firms. The forecast errors produced by all models for the time-series sample appear smaller (no significance tests are performed) than the forecast errors from the cross-sectional sample. Table 10, panel B compares the forecast errors of each model. The forecast errors produced by CFRW and CFREG are not significantly different from each other. ACCPAR produces significantly higher median and mean forecast errors than ACCREG. In no instances does an accrual model produce lower forecast errors than a cash flow model. Therefore, as in the cross-sectional sample, no positive incremental predictive ability is detected, on average, for the time-series sample.

Table 10, panel C compares the absolute forecast errors of each model for firms in the lowest (highest) deciles of IRVOL, EARNVOL, and SALESVOL (AVGTA). In no instance does an accrual-based model produce lower absolute forecast errors than a cash-flow-based model, even for firms in the extreme deciles based on firm characteristics. Therefore, while the incremental predictive ability of accrual-based models over cash-flow-based-models is decreasing in IRVOL, SALESVOL, and EARNVOL (as shown in table 6), no positive incremental predictive ability can be detected for firms in the lowest deciles of IRVOL, SALESVOL, and EARNVOL.

6. Conclusions and avenues for future research

This paper builds upon the model of Barth, Cram and Nelson (2001) to incorporate the cash flow implications of growth in future sales and allows management to impound their forecasts of future sales into ending inventory. The paper assesses the ability of ending inventory to be used as a predictor of future sales, and hence future cash flows. To measure the effect on cash flow predictions of the error in which inventory predicts future cash flows, I compare the forecasts generated when using actual sales versus sales predicted through ending inventory. I do not find evidence that the effect of sales estimation error is less for firms with a stable ratio of inventory to future sales.

This study does not find evidence that accrual models contain positive incremental predictive ability over cash-flow-only models in predicting one-year-ahead cash flows. However, the incremental forecast ability of accrual models (whether using actual sales or sales predicted by ending inventory) is increasing (decreasing) with firm stability (volatility). While the incremental predictive ability varies with firm characteristics, the study fails to find positive incremental predictive ability for firms in the lowest deciles based on volatility.

This study provides evidence that suggests prior research used an inappropriate cash-flow-based model as the benchmark to measure the incremental predictive ability of accrual-based models. Kim and Kross (2005) and Lev et al. (2005) use a cash flow model where cash flows are regressed on prior cash flows. Kim and Kross (2005) conclude that earnings contain incremental predictive ability beyond that of cash flows based on this cash flow model. However, this study finds that a random walk model of cash flows produces lower out-of-sample forecast errors than a cross-sectional regression of cash flows on prior cash flows and thus should serve as the benchmark forecast method for measuring accrual models' incremental predictive ability.

In addition to the one-year ahead cash flow examined in this paper, accruals may be predictive of cash flows further in the future. Previous studies have applied models similar to the model in this paper (with the addition of long-term accruals) while attempting to predict long-term cash flows. Similar to the analysis in this paper, future research could investigate the ability of long-term accruals to predict future sales and hence future cash flows. One long-term accrual that may contain information about future growth (decline) is capital expenditures in excess (short) of the amount needed to maintain the current operating capacity. Deferred tax (especially the change in a deferred tax asset valuation allowance) may also contain information about future sales. A model using long-term accruals to predict future sales may be a more powerful prediction model than the accrual models developed thus far.

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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	Fraction of annual sales uncollected at year-end measured as AR_t/S_t.
β	Fraction of annual inventory purchases (PURCH) and operating expenses (OE) unpaid at year end measured as AP_t / ($PURCH_t + OE_t$).
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
Descriptive Statistics for Sample of Firms

Panel A: Distribution of Financial Statement Variables (Millions)

Variable	Median	Mean	Standard Error
CFO	10.116	189.119	5.686
ΔAR	0.957	11.189	1.252
ΔInv	0.608	6.802	0.683
ΔAP	0.167	4.458	1.187
ΔAccExp	0.374	9.811	0.910
ΔAccIT	0.000	1.232	0.399
Inv	31.975	233.124	5.300
Sales	216.021	2112.260	55.818
AvgTA	170.334	1901.510	56.475

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*
Sales	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. All variables are defined in table 1.

Table 2 (cont.)
Descriptive Statistics for Sample Firms

Panel C: Distribution of parameters and firm characteristics

Variable	Median	Mean	Standard Error
α	0.154	0.166	0.00062
β	0.148	0.160	0.00048
γ	0.225	0.281	0.00327
π	0.334	0.357	0.00109
λ	0.231	0.274	0.00134
IRVOL	0.034	0.055	0.00218
SALESVOL	0.211	0.261	0.00436
EARNVOL	0.055	0.073	0.00125

All variables are defined in table 1.

Table 2 (cont.)
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. All variables are defined in table 1.

Table 3
Time-Series Sample Selection

Data Requirement	Number of Firms
Positive total assets each year from 1978 – 2004	1,226
Delete firms not in Wholesaling, Retailing, or Manufacturing	-561
Delete firms without the required cash flow or accrual information.[1]	-116
Delete firms where total assets increased by more than 30% over the prior year's total assets for any year from 1979 through July, 1988 (i.e. any year prior to the requirement to issue a Statement of Cash Flows).[2]	-298
Delete firms where the absolute value of income/loss from discontinued operations is greater than 30% of the absolute value of earnings before extraordinary items for any year from 1979 through July, 1988.[2]	-58
Firms in Time-Series Sample	**192**

[1]Firms are required to have cash flow from operations, change in accounts receivable, change in accounts payable, change in accrued expense, change in inventory, level of ending inventory, positive sales, positive cost of goods sold, and positive selling, general and administrative expense.

[2]Hribar and Collins (2002) find that mergers and acquisitions and divestitures produce significant error in estimating cash flows from operations when using the balance sheet approach. Since cash flows were estimated using the balance sheet for years ending prior to July 1988, all firms experiencing mergers and acquisitions and divestitures from 1979 through July, 1988 are excluded. Firms are assumed to have experienced a merger or acquisition if total assets increase by greater than 30% in any one year. Firms are assumed to have experienced a divestiture if the absolute value of income/loss from discontinued operations is greater than 30% of the absolute value of earnings before extraordinary items. Hribar and Collins also find that gains and loss on foreign currency translation creates noise in the cash flow estimations. However, this noise appears random and does not have a biasing effect. Since nearly all firms in the manufacturing, retailing, and wholesaling firms have gains and losses on foreign currency translations, these firms are not eliminated.

Table 4
Descriptive Statistics for
Time-Series Sample Firms

Panel A: Distribution of Financial Statement Variables (Millions)

Variable	Median	Mean	Standard Error
CFO	49.331	395.700	20.036
ΔAR	1.963	25.809	3.979
ΔINV	1.553	18.367	3.113
ΔAP	0.507	11.101	6.595
ΔAccExp	0.382	15.415	6.128
ΔAccIT	0.000	1.244	1.741
Inv	108.210	516.107	18.427
Sales	724.732	4235.350	193.251
AvgTA	472.432	3543.800	165.472

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

	CFO	chAR	chINV	chAP	chAccExp	chAccIT	Inv	Sales
CFO	--	-0.2130 <.01	-0.3094 <.01	0.0073 0.61	0.1555 <.01	0.1800 <.01	-0.2023 <.01	0.0925 <.01
chAR	-0.1552 <.01	--	0.2433 <.01	0.3464 <.01	0.1226 <.01	0.1087 <.01	0.0725 <.01	0.0827 <.01
chINV	-0.2310 <.01	0.3066 <.01	--	0.2833 <.01	0.0698 <.01	0.0201 0.16	0.3137 <.01	0.1292 <.01
chAP	0.0558 <.01	0.3559 <.01	0.3163 <.01	--	-0.2450 <.01	0.0483 <.01	0.0892 <.01	0.1109 <.01
chAccExp	0.1773 <.01	0.1979 <.01	0.1320 <.01	-0.0203 0.16	--	0.0334 0.02	0.0184 0.20	0.0726 <.01
chAccIT	0.1790 <.01	0.1430 <.01	0.0302 0.04	0.0909 <.01	0.1032 <.01	--	-0.0177 0.22	0.0081 0.58
Inv	-0.1747 <.01	0.1083 <.01	0.2972 <.01	0.0910 <.01	0.0456 <.01	-0.0145 0.31	--	0.3730 <.01
Sales	0.1453 <.01	0.1603 <.01	0.1854 <.01	0.1305 <.01	0.1399 <.01	0.0252 0.08	0.4999 <.01	--

Correlations above (below) the diagonal are Pearson (Spearman) correlations. The bottom number in each cell is a two-tail p-value. All variables are defined in table 1.

Table 4 (cont.)
Descriptive Statistics for
Time-Series Sample Firms

Panel C: Distribution of Parameters and Firm Characteristics

Variable	Median	Mean	Standard Error
α	0.144	0.150	0.00123
β	0.125	0.136	0.00099
γ	0.228	0.278	0.00353
π	0.313	0.336	0.00199
λ	0.197	0.217	0.00175
IRVOL	0.036	0.048	0.00439
SALESVOL	0.232	0.292	0.01552
EARNVOL	0.040	0.051	0.00398

All variables are defined in table 1.

Table 4 (cont.)
Descriptive Statistics for
Time-Series Sample Firms

Panel D: Correlations of Parameters and Firm Characteristics

	α	**β**	**γ**	**π**	**λ**	**IRVOL**	**AVGTA**	**SALESVOL**	**EARNVOL**
α	--	0.3436 <.01	0.0955 0.19	0.0884 0.22	0.0626 0.39	0.0846 0.24	0.0278 0.70	-0.3433 <.01	0.0086 0.91
β	0.3460 <.01	--	0.0294 0.69	0.1414 0.05	-0.0023 0.97	-0.0185 0.80	0.1647 0.02	-0.2513 <.01	0.0224 0.76
γ	0.3668 <.01	0.0763 0.29	--	0.3519 <.01	0.3500 <.01	0.8098 <.01	-0.1128 0.12	-0.1677 0.02	0.1889 0.01
π	0.1794 0.01	0.0646 0.37	0.4254 <.01	--	0.8555 <.01	0.0223 0.76	-0.0537 0.46	-0.2227 <.01	0.0096 0.89
λ	0.1120 0.12	-0.0429 0.55	0.4204 <.01	0.8803 <.01	--	0.0996 0.17	-0.1257 0.08	-0.0478 0.51	0.0923 0.20
IRVOL	0.3198 <.01	0.0762 0.29	0.6668 <.01	0.0404 0.58	0.0659 0.36	--	-0.0790 0.28	-0.0481 0.51	0.1831 0.01
AVGTA	-0.0085 0.91	0.4598 <.01	-0.2947 <.01	0.0137 0.85	-0.1323 0.07	-0.3222 <.01	--	-0.0639 0.38	-0.0826 0.25
SALESVOL	-0.3800 <.01	-0.2372 <.01	-0.2238 <.01	-0.2118 <.01	-0.0243 0.74	-0.0212 0.77	-0.1773 0.01	--	0.0494 0.50
EARNVOL	0.1274 0.08	-0.0004 0.99	0.2337 <.01	0.0788 0.28	0.1242 0.09	0.3856 <.01	-0.3107 <.01	0.2192 <.01	--

Correlations above (below) the diagonal are Pearson (Spearman) correlations. Figures in italics are two-tailed p-values. All variables are defined in Table 1.

Table 5
Cash Flow Predictions when Future Sales is Forecasted using Ending Inventory

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 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):

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

Panel A: Coefficient Estimates

	CFREG	ACCPAR	ACCREG
Intercept	.2720 *2.51*		-.1635 *-1.85*
CFO_{t-1}	.7476 *45.31*	1.000	1.000
ΔINV_{t-1}		.8425 *432.95*	.4915 *17.69*
INV_{t-1}		1.1085 *22.31*	.0225 *1.92*
S_{t-1}		-.0575 *-17.46*	-.0002 *-0.15*
$E\Delta Sales2_{t-1}$		-.1060 *-66.98*	-.0124 *-3.34*
R^2	.4858	N/A	.1784

Figures in italics are t-statistics. 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 coefficients reported are the mean coefficients across all industries and years. 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. All variables are defined in table 1.

Table 5 (cont.)
Cash Flow Predictions when Future Sales is Forecasted using Ending Inventory

Panel B: Absolute Out-of-Sample Forecast Errors

	Cash Flow Forecast Error ($Millions)		Cash Flow Forecast Error Scaled by AvgTA	
Model	**Mean**	**Median**	**Mean**	**Median**
CFRW	73.01	9.30	.0768	.0493
CFREG	91.25	9.90	.0785	.0538
ACCPAR	164.28	13.32	.1193	.0736
ACCREG	83.36	9.54	.0802	.0521

Panel C: Comparison of Predictive Abilities between Models

Models Compared	**Expected Sign**	**Mean Difference***	**Median Difference***
CFRW less CFREG	?	-.0017 (<.01)	-.0019 (<.01)
CFRW less ACCPAR	+	-.0425 [>.99]	-.0167 [>.99]
CFRW less ACCREG	+	-.0034 [>.99]	-.0012 [>.99]
CFREG less ACCPAR	+	-.0409 [>.99]	-.0150 [>.99]
CFREG less ACCREG	+	-.0017 [.99]	.0020 [<.01]
ACCPAR less ACCREG	?	.0392 (<.01)	.0140 (<.01)

***A positive difference indicates the second model listed has incremental predictive ability beyond that of the first model listed.**

Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. P-values for differences in means are based on a paired t-test. P-values for median differences are based on a paired sign test.

Table 6
Effect of Firm Characteristics on Prediction Models
when Sales is Forecasted using Ending Inventory

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

		IRVOL		EARNVOL		SALESVOL		AVGTA
CFRW	?	0.4123 (<.01)	+	0.5988 [<.01]	+	0.4014 [<.01]	-	-0.4608 [<.01]
CFREG	?	0.3254 (<.01)	+	0.5648 [<.01]	+	0.3739 [<.01]	-	-0.4069 [<.01]
ACCPAR	+	0.2825 [<.01]	+	0.5366 [<.01]	+	0.2958 [<.01]	-	-0.2926 [<.01]
ACCREG	+	0.4432 [<.01]	+	0.6197 [<.01]	+	0.4232 [<.01]	-	-0.4753 [<.01]

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

		IRVOL		EARNVOL		SALESVOL		AVGTA
CFRW less CFREG	?	0.2858 (<.01)	?	0.1805 (<.01)	?	0.1428 (<.01)	?	-0.1841 (<.01)
CFRW less ACCPAR	-	0.0333 [0.94]	?	-0.1131 (<.01)	?	0.0114 (0.58)	+	-0.0683 [>.99]
CFRW less ACCREG	-	-0.0566 [0.01]	?	-0.0713 (0.08)	?	-0.0435 (0.04)	+	0.0215 [0.11]
CFREG less ACCPAR	-	-0.0563 [<.01]	?	-0.1728 (<.01)	?	-0.0362 (0.08)	+	-0.0145 [0.80]
CFREG less ACCREG	-	-0.2417 [<.01]	?	-0.1800 (<.01)	?	-0.1339 (<.01)	+	0.1438 [<.01]
ACCPAR less ACCREG	?	-0.0651 (<.01)	?	0.0744 (0.04)	?	-0.0339 (0.11)	?	0.1008 (<.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. All variables are defined in table 1.

Table 7
Cash Flow Predictions using
Actual Future Sales

Cash flow-based random walk model (CFRW):

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

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

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

Accrual-based parameter model with actual future sales (ACCPARA*):

$$E\left(CFO_{i,t+1}\right) = CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t} + (1-\beta)\Delta INV_{i,t} + \left[(1-\alpha) - (1-\beta)\left[(1-\pi) + \lambda\right]\right]G_{i,t+1} - (1-\beta)\gamma(1-\pi)G_{i,t+2}$$

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

$$E\left(CFO_{i,t+1}\right) = \theta_0 + CFO_{i,t} + \Delta AR_{i,t} - \Delta AP_{i,t} - \Delta AccExp_{i,t} - \Delta AccIT_{i,t} + \theta_1 \Delta INV_{i,t} + \theta_2 G_{t+1} + \theta_3 G_t$$

Panel A: Coefficient Estimates

	CFREG*	ACCPARA*	ACCREG*
Intercept	-.4704 *-6.11*		-.1104 *-1.45*
CFO	.5276 *23.30*	1.000	1.000
ΔINV		.8425 *432.95*	.4414 *12.79*
S_t	.0266 *7.35*		
S_{t+1}	.0059 *2.10*		
G_t		.0575 *17.46*	.0416 *7.16*
G_{t+1}		-.1060 *-66.98*	-.0034 *-1.13*
R^2	.5792	N/A	.2280

Figures in italics are t-statistics. 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 coefficients reported are the mean coefficients across all industries and years. 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. All variables are defined in table 1.

Table 7 (cont.)
Cash Flow Predictions using
Actual Future Sales

Panel B: Absolute Out-of-Sample Forecast Errors

	Cash Flow Forecast Error ($Millions)		Cash Flow Forecast Error Scaled by AvgTA	
Model	**Mean**	**Median**	**Mean**	**Median**
CFRW	73.01	9.30	.0768	.0493
CFREG*	83.69	9.06	.0756	.0504
ACCPAR*	76.39	9.34	.0812	.0496
ACCREG*	77.92	9.16	.0790	.0499

Panel C: Comparison of Predictive Abilities between Models

Models Compared	**Exp. Sign**	**Mean**	**Median**
CFRW – CFREG	?	.0008 (.05)	.0004 (.17)
CFRW – ACCPAR*	+	-.0048 [>.99]	.0001 [.39]
CFRW – ACCREG*	+	-.0026 [>.99]	.0006 [.02]
CFREG* – ACCPAR*	+	-.0034 [.99]	.0007 [.01]
CFREG* – ACCREG*	+	-.0056 [.83]	.0001 [.40]
ACCPAR* – ACCREG*	?	.0022 (<.01)	.0003 (.31)

Mean (Median) in panel c is the difference in mean (median) absolute cash flow forecast errors (scaled by AvgTA) between the two models listed in column one. A positive difference indicates the second model listed has incremental predictive ability beyond that of the first model listed.

Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. P-values for differences in means are based on a paired t-test. P-values for median differences are based on a paired sign test.

Table 8
Effect of Firm Characteristics on Prediction Models
using Actual Future Sales

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

Model		IRVOL		EARNVOL		SALESVOL		AVGTA
CFRW	?	0.4124 (<.01)	+	0.5988 [<.01]	+	0.4014 [<.01]	-	-0.4608 [<.01]
CFREG	?	0.3326 (<.01)	+	0.5572 [<.01]	+	0.4002 [<.01]	-	-0.4347 [<.01]
ACCPAR	?	0.5236 (<.01)	+	0.6125 [<.01]	+	0.4507 [<.01]	-	-0.4651 [<.01]
ACCREG	?	0.4413 (<.01)	+	0.5949 [<.01]	+	0.4320 [<.01]	-	-0.4781 [<.01]

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

		IRVOL		EARNVOL		SALESVOL		AVGTA
CFRW – CFREG*	?	0.1810 (<.01)	?	0.1448 (<.01)	?	0.0646 (<.01)	?	-0.1069 (<.01)
CFRW – ACCPAR*	?	-0.2201 (<.01)	?	-0.1037 (<.01)	?	-0.0861 (<.01)	+	0.0381 [0.02]
CFRW – ACCREG*	?	-0.0977 (<.01)	?	-0.0543 (0.02)	?	-0.0732 (<.01)	+	0.0716 [<.01]
CFREG* – ACCPAR*	?	-0.3289 (<.01)	?	-0.1895 (<.01)	?	-0.1338 (<.01)	+	0.1087 [<.01]
CFREG* – ACCREG*	?	-0.2351 (<.01)	?	-0.1595 (<.01)	?	-0.1240 (<.01)	+	0.1474 [<.01]
ACCPAR* – ACCREG*	?	0.1845 (<.01)	?	0.0628 (<.01)	?	0.0468 (0.03)	?	0.0098 (0.60)

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. All variables are defined in table 1.

Table 9
Effect of using Estimated versus Actual
Sales on Cash Flow Predictions
(Table 5 minus Table 7)

Panel A: Change in Absolute Out-of-Sample Forecast Error

		Cash Flow Forecast Error ($Millions)		Cash Flow Forecast Error (scaled by AvgTA)	
Model	**Exp. Sign**	**Mean**	**Median**	**Mean**	**Median**
CFREG – CFREG*	+	7.93 [<.01]	0.30 [<.01]	.0025 [<.01]	.0035 [<.01]
ACCPAR – ACCPAR*	+	84.82 [<.01]	1.47 [<.01]	0.0379 [<.01]	0.0153 [<.01]
ACCREG – ACCREG*	+	6.37 [<.01]	0.11 [<.01]	0.0006 [0.07]	0.0013 [<.01]

Panel B: Spearman correlation between increase in scaled forecast errors and firm characteristics

		IRVOL		SALESVOL		EARNVOL		AVGTA
CFREG – CFREG*	?	-0.0832 (<.01)	?	-0.0507 (0.02)	?	-0.0134 (0.53)	?	0.0796 (<.01)
ACCPAR – ACCPAR*	+	-0.1928 [>.99]	?	-0.0788 (<.01)	?	0.0214 (0.31)	?	0.1457 (<.01)
ACCREG – ACCREG*	+	-0.0416 [0.98]	?	-0.0279 (0.19)	?	0.0295 (0.16)	?	0.0536 (<.01)

Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values.

Amounts reported in this table are the differences between forecast errors reported in tables 5 and 7. A positive number in panel A reflects the increase in forecast error that results from using forecasted sales (or no sales in the case of CFREG) versus actual sales. A positive number in panel B indicates the effect of sales estimation error is increasing in the firm characteristic.

Table 10
Cash Flow Predictions for Time-Series
Sample of Firms when Future Sales is
Forecasted using Ending Inventory

Panel A: Absolute Out-of-Sample Forecast Errors

	Cash Flow Forecast Error ($Millions)		Cash Flow Forecast Error Scaled by AvgTA	
Model	**Mean**	**Median**	**Mean**	**Median**
CFRW	256.83	29.34	0.0542	0.0356
CFREG	277.28	29.54	0.0526	0.0347
ACCPAR	366.59	38.54	0.0676	0.0469
ACCREG	315.21	26.96	0.0603	0.0407

Panel B: Comparison of Predictive Abilities between Models

Models Compared	Expected Sign	Mean Difference*	Median Difference*
CFRW less CFREG	?	.0016 (0.28)	-.0012 (0.09)
CFRW less ACCPAR	+	-.0135 [>.99]	-.0080 [>.99]
CFRW less ACCREG	+	-.0061 [>.99]	-.0029 [>.99]
CFREG less ACCPAR	+	-.0150 [>.99]	-.0085 [>.99]
CFREG less ACCREG	+	-.0076 [>.99]	.0033 [>.99]
ACCPAR less ACCREG	?	.0074 (<.01)	.0052 (<.01)

The forecast errors are calculated by applying each model listed in table 5 to a firm-specific time-series of data starting in 1979. Forecasts of cash flows are performed for years 2000 through 2004.

***A positive difference indicates the second model listed has incremental predictive ability beyond that of the first model listed.**

Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. P-values for differences in means are based on a paired t-test. P-values for median differences are based on a paired sign test.

Table 10 (cont.)
Cash Flow Predictions for Time-Series Sample of Firms when Future Sales is Forecasted using Ending Inventory

Panel C: Incremental Predictive Abilities for Firms in the Highest or Lowest Deciles of Each Firm Characteristic

Models Compared	Expected Sign	IRVOL (Decile 1) Mean Diff	IRVOL (Decile 1) Median Diff	EARNVOL (Decile 1) Mean Diff	EARNVOL (Decile 1) Median Diff	SALESVOL (Decile 1) Mean Diff	SALESVOL (Decile 1) Median Diff	AVGTA (Decile 10) Mean Diff	AVGTA (Decile 10) Median Diff
CFRW less CFREG	?	0.0009	-0.0008	-0.0060	-0.0037	-0.0002	0.0000	-0.0017	-0.0004
		(0.71)	(0.50)	(0.19)	(0.12)	(0.92)	(1.00)	(0.56)	(0.50)
CFRW less ACCPAR	+	-0.0213	-0.0108	-0.0128	-0.0070	-0.0138	-0.0061	-0.0221	-0.0132
		[>.99]	[>.99]	[0.97]	[0.98]	[>.99]	[0.98]	[>.99]	[>.99]
CFRW less ACCREG	+	-0.0085	-0.0096	-0.0075	-0.0062	-0.0040	-0.0063	-0.0104	-0.0046
		[0.98]	[0.94]	[0.90]	[0.87]	[0.89]	[0.94]	[>.99]	[0.94]
CFREG less ACCPAR	+	-0.0222	-0.0225	-0.0068	-0.0047	-0.0135	-0.0114	-0.0204	-0.0146
		[>.99]	[0.98]	[0.85]	[0.59]	[>.99]	[0.98]	[>.99]	[>.99]
CFREG less ACCREG	+	-0.0095	-0.0106	-0.0015	0.0006	-0.0038	-0.0079	-0.0088	-0.0101
		[>.99]	[0.94]	[0.5728]	[0.50]	[.84]	[0.87]	[0.97]	[0.94]
ACCPAR less ACCREG	?	0.0128	0.0073	0.0054	0.0085	0.0097	0.0047	0.0117	0.0077
		(.04)	[.04]	(0.56)	(.26)	(.09)	(0.26)	(0.07)	(0.12)

The table reports the difference in forecast errors from each model for firms in the lowest (highest) decile of IRVOL, EARNVOL, and SALESVOL (AVGTA). The forecast errors are calculated by applying the models to firm-specific time-series of data starting in 1979. Forecasts of cash flows for 2000 through 2004 were performed for each firm. A positive difference indicates the second model listed has incremental predictive ability beyond that of the first model listed.

Figures in parenthesis are two-tailed p-values. Figures in brackets are one-tailed p-values. P-values for differences in means are based on a paired t-test. P-values for median differences are based on a paired sign test. All variables are defined in table 1.