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The Predictive Ability of Statistically-Based Cash-Flow Models

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I. Introduction

We provide an assessment of the information content of earnings by testing the predictive ability of statistically-based cash flow prediction models developed originally by Dechow et al. (1998) and subsequently refined by Barth et al. (2001). Both studies model the time-series properties of income statement and balance sheet components and develop lead/lag relationships between net earnings and/or accruals with respect to future realizations of cash flow from operations (CFO). Such modeling exercises provide *descriptive* support for the Financial Accounting Standards Board (FASB's) normative assertions with regard to net earnings pre-saging CFO. Specifically, FASB has asserted that information about earnings and its components has more predictive power relative to future CFOs than current CFO (FASB 1978). An assessment of the inter-temporal predictive ability of statistically-based CFO prediction models should provide salient information to researchers, standard setters and financial analysts interested in deriving relatively accurate CFO predictions. Consistent with this notion, FASB (1978) stresses the importance of predicting CFO data:

> …..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 enterprises(para. 37).

In this context, Kim and Kross (2005) distinguish sharply between in-sample descriptive fit versus out-of-sample predictive evidence. The former is captured by adjusted R^2 of the CFO prediction models while the latter is measured by the accuracy of *ex-ante* CFO extrapolations derived from these models. Specifically, these forecasted CFO values are then compared to their corresponding actual CFO values using data from an inter-temporal holdout period that was not employed in model estimation. Assessment of forecast accuracy is then conducted within the aforementioned holdout period. Kim and Kross also state that in-sample descriptive fit does not necessarily imply a good out-of-sample forecast since the model can overfit the data (Kim and Kross 2005: 767). Watts and Leftwich (1977), among others, have referred to this relationship as the so-called "regression fallacy." Therefore, caution must be exercised in imputing predictive characteristics to alternative CFO prediction models based *solely* on in-sample descriptive goodness-of-fit metrics.

We assess the forecast accuracy of statistically-based cash-flow prediction models on *ex-ante* cash-flow forecasts generated using data from a true holdout period (i.e., the 20 quarters within the 2001-2005 interval) not employed in model estimation. Furthermore, we analyze the impact of estimating such models in a dual fashion: cross-sectionally, which imposes constant parameter values across firms and time, and on a time-series basis that allows parameter values to vary on a firm-specific basis. Our predictive results provide compelling evidence supportive of the utilization of time-series versus cross-sectional estimation of statistically-based quarterly CFO prediction models. Our empirical results also support the use of relatively parsimonious CFO prediction models that rely upon lagged values of net earnings before extraordinary items as independent variables as opposed to more complex models (i.e., the disaggregated accrual models) that employ lagged values of disaggregated components of net earnings. These findings are robust across individual quarters (1 thru 4), years (2001-2005), and on a pooled basis across all quarters and years in the 2001-2005 holdout period. While our predictive findings differ from the descriptive evidence provided by Barth et al. (2001), they are consistent with "Occam's razor" and the principle of parsimony.[1] Zhang, Cao, and Schniederjsans (2004) cite research consistently finding that relatively complex prediction models that fit well descriptively (i.e., adjusted R^2) do not perform well in out-of-sample predictive tests in an inter-temporal holdout period across diverse predictive settings. Our predictive results pertain regardless of whether the models are estimated using undeflated or deflated variables. We also provide additional analyses where we expand greatly the primary sample of 296 firms to 1,090 firms yielding 21,800 firm/quarter CFO predictions by eliminating the stringent data requirements of the disaggregated accrual model due to its relatively poor predictive performance on the primary sample of firms. The results of our primary analysis are validated on the expanded sample of firms thereby greatly enhancing the external validity of our empirical findings.

The remainder of the paper is outlined as follows. Section 2 provides a background serving to underscore the importance of CFO predictions. Section 3 relates the study to extant research on CFO prediction models. Section 4 discusses the research design and provides some descriptive statistics on model parameters. Section 5 provides an assessment of predictive performance. Section 6 presents predictive results on the expanded sample. Finally, section 7 provides a summary of the findings, concluding remarks, and some suggestions for future research.

2. Background

While the accounting literature is replete with empirical studies that assess the predictive performance of *annual* cash-flow prediction models (Dechow et al. 1998, Barth et al. 2001, and Kim and Kross, 2005) relatively recent work assessing the predictive performance of *quarterly* cash-flow prediction models is virtually non-existent.[2] Modeling of quarterly versus annual cash-flow data may be more complicated due to the frequency with which the data are reported introducing the potential for incremental measurement error, among other factors (Dechow et al. 1998: 145). Nevertheless, modeling of quarterly data shortens the measurement interval thereby allowing for more timely cash-flow forecasts than exclusive reliance upon annual data as well as minimizing sampling variation in parameter estimation due to working with considerably longer databases. The assessment of the tradeoffs associated with using quarterly versus annual data is essentially empirical.

In a related setting, Brown (1993), among others, discusses how "Occam's razor" and the principle of parsimony mitigate against the predictive performance of relatively complex quarterly earnings prediction models versus relatively parsimonious alternatives when quarterly earnings prediction models are estimated on a time-series basis. Brown summarizes empirical evidence pertaining to how parsimonious quarterly earnings ARIMA models typically outperform more complex firm-specific ARIMA alternatives in time-series work based upon quarterly earnings data. In an analogous manner, we assess the predictive power of relatively simple CFO prediction models that employ aggregate earnings as independent variables versus relatively complex CFO prediction models that employ disaggregated components of earnings as independent variables. Thus, the purpose of this paper, therefore, is to provide new empirical evidence pertaining to the predictive performance of statistically-based quarterly cash-flow prediction models.[3]

The predictive ability of statistically-based models using quarterly CFO is of considerable interest to both accounting researchers, standard setters, and members of the investment community. Barth (2006) argues that the predictability of income itself is less important than income's ability to predict future CFO. In fact, she suggests that CFO prediction is inextricably related to the objectives of financial reporting and links it to the International Accounting Standard Board's (IASB's) apparent focus on using more estimates of the future in the measurement of assets and liabilities. An assessment of the predictive ability of statistically-based quarterly cash-flow prediction models is crucial in this setting since such models may be applied to a large set of firms, generate multi-step ahead quarterly CFO predictions, and have the potential to be more accurate than extant sell-side analysts' quarterly CFO forecasts.[4] Since financial analysts must typically generate n-step ahead CFO forecasts when employing discounted cash-flow valuation methodologies which are elucidated in financial statement analysis texts (Palepu and Healy, 2008 and Penman, 2007, among others), the aforementioned predictive results should also be of particular interest to the investment community.

Analysts' quarterly CFO forecasts are currently unavailable in sufficient quantities to perform predictive ability assessments on the relatively large number of firms that we examine in our expanded sample thereby enhancing interest in the statistically-based modeling of quarterly CFO. For example, Barniv et al. (2005) provide relatively recent empirical evidence documenting that less than 1% of their total sample of U. S. firms had quarterly CFO forecasts attributed to sell-side analysts. DeFond and Hung (2003) speculate that analysts' quarterly CFO forecasts are relatively rare due to the inherent difficulty in predicting CFO over such short time intervals. Yet, users interested in firm valuation methodologies typically require such multi-step ahead quarterly CFO forecasts. We are unaware, however, of any publicly available source of multi-step ahead quarterly CFO forecasts attributed to analysts.

3 . Relation to Prior Research

Annual work assessing the efficacy of cash-flow prediction models (Dechow et al. 1998, Barth et al. 2001, and Kim and Kross 2005) provides a useful background against which the predictive performance of quarterly CFO prediction models might be discussed. Dechow et al. (1998) employed firm-specific time-series regression models where future values of annual CFO were regressed upon current annual CFO and aggregate annual net earnings during the 1963–1992 test period. Since most of their time-series data pre-dated the inception of SFAS No. 95, they employed an algorithm to proxy the annual CFO series. Dechow et al. found that aggregate annual earnings were consistently useful in forecasting future annual CFOs beyond the information contained in the time series of past annual CFO values. Their predictive findings are tested on both an in-sample and out-of-sample basis and are generally consistent.

While Barth et al. (2001) adopted the overall modeling structure popularized by Dechow et al. (1998), there were some important methodological refinements. First, Barth et al.'s period of analysis (1987–1996) allowed them to employ annual CFO data reported by SFAS No. 95 as opposed to using an algorithm to proxy the CFO series. Second, Barth et al. disaggregated earnings into cash flows and six major accrual components (e.g., change in accounts receivable, change in accounts payable, change in inventory, depreciation, amortization, and other accruals) to determine whether employment of accrual components in CFO prediction models enhanced explanatory power. Third, they estimated their CFO prediction models cross-sectionally as opposed to using the time-series approach employed by Dechow et al. Barth et al.'s primary findings revealed that annual CFO prediction models that employ disaggregated earnings components (i.e., disaggregated accrual models) provided superior in-sample descriptive goodness of fit (e.g., adjusted R^2) vis-à-vis CFO prediction models that use aggregate earnings and/or cash flows. Whether enhanced descriptive fit of CFO models translates into superior predictive performance in an out-of-sample, inter-temporal holdout period is an empirical issue not directly addressed directly by Barth et al.

Kim and Kross (2005) also adopted the regression models of Dechow et al. and employed the cross-sectional estimation procedure used by Barth et al. to examine the predictive power of annual CFO prediction models over a 28-year period. In addition to using descriptive goodness-of-fit criteria similar to Barth et al., they also assessed predictive performance using an "out-of-sample" inter-temporal holdout period. They found that the predictive performance of their models was generally increasing in forecast accuracy across time. However, Kim and Kross did not estimate their annual CFO prediction models on a time-series basis like Dechow et al. nor employ disaggregate accrual components similar to Barth et al.

4. Research Design

4.1 SAMPLE FIRMS

We obtained financial statement data from the quarterly *Compustat* industrial and research tapes spanning the interval from the first quarter, 1989 to the fourth quarter, 2005. Initially, sample firms met two criteria: 1) they had complete time-series data for two series: quarterly CFO reported in accordance with SFAS No. 95 and quarterly net earnings before extraordinary items, and 2) they had complete time-series data necessary to operationalize Barth et al.'s disaggregated accrual prediction model, namely accounts receivable, accounts payable, inventory, depreciation, amortization, and other accruals all reported on a quarterly basis. Kim and Kross (2005), among others, argue that CFO reported under SFAS No. 95 guidelines are less subject to measurement error than proxies computed in earlier work such as the data employed by Lorek and Willinger (1996). Hribar and Collins (2002) provide substantiating evidence that there are systematic differences between reported CFO and proxies derived from simplistic algorithms further enhancing the desirability of using reported CFO data in this setting.

The implementation of the aforementioned sampling filters resulted in a primary sample of 296 firms on which we generate 5,920 firm/quarter CFO predictions. In additional analyses reported in section 6 we eliminated the disaggregated accrual model with its stringent quarterly financial component data requirements due to its relatively poor predictive performance and present predictive results based upon a greatly expanded sample of 1,090 firms resulting in 21,800 firm/quarter CFO predictions to enhance generalizability.

Table 1 lists the twenty-four industries that had five or more firms represented in the primary sample. For example, the four industries with the greatest two-digit SIC code representation are: Electronic and Other Electrical Equipment (n=32, 10.8% of sample); Chemicals and Allied Products (n=31, 10.5% of sample); Machinery except Electrical (n=19, 6.4% of sample); and Business Services (n=16, 5.4% of sample). Additionally, there were 23 other two-digit SIC codes that were represented, each of them having fewer than 5 sample firms. Such widespread industry representation underscores the pervasive impact of SFAS No. 95's reporting requirements.

Table 1
Two-Digit SIC Codes Represented in the Sample

This table lists all twenty-four two-digit SIC codes that have five or more firms represented in the primary sample of 296 firms. Additionally, there were twenty-three other two-digit SIC codes that were represented, each of them having fewer than five sample firms.

SIC Code	Industry	Number of Firms
36	Electronic and Other Electrical Equipment	32
28	Chemicals and Allied Products	31
35	Machinery, Except Electrical	19
73	Business Services	16
38	Instruments and Related Products	14
13	Oil & Gas Extraction	13
20	Food and Kindred Products	13
50	Wholesale Trade – Durable Goods	10
29	Petroleum and Coal Products	8
56	Apparel and Accessory Stores	8
26	Paper and Allied Products	7
33	Primary Metal Industries	7
48	Communication	7
53	General merchandise Stores	7
54	Food Stores	7
39	Miscellaneous Manufacturing Industries	6
45	Transportation by Air	6
49	Electric, Gas and Sanitary Services	6
51	Wholesale Trade – Nondurable Goods	6
58	Eating and Drinking Places	6
34	Fabricated Metal Products	6
27	Printing and Publishing	5
37	Transportation Equipment	5
80	Health Services	5
And 23 other two-digit SIC Codes with less than 5 firms each		46
	Total Sample	296

4.2 CASH-FLOW PREDICTION MODELS

We employ two CFO prediction models originally developed by Dechow et al. (1998) and refined by Barth et al. (2001): an aggregate earnings model [Equation (1)] and a disaggregated accrual model [Equation (2)] which are stipulated below:

$$CFO_{i,\,t+1} = b_0 + \sum_{\tau=0}^{k} b_{t-\tau}\ EARN_{i,\,t-\tau} + u_{it} \qquad (1)$$

$$CFO_{i,\,t+1} = c_0 + c_1\,CFO_{it} + c_2\,\Delta AR_{it} + c_3\,\Delta INV_{it} + c_4\,\Delta AP_{it} + c_5\,DEPR_{it} +$$

$$c_6\,AMORT_{it} + c_7\,OTHER_{it} + u_{it} \qquad (2)$$

where i and t denote firm and year, τ ranges between 0 and 2, EARN is net earnings before extraordinary items, AR is accounts receivable, INV is inventory, AP is accounts payable, DEPR is depreciation expense, AMORT is amortization expense, and OTHER is the aggregate of remaining accruals not specifically detailed above.

We generate one thru twenty step-ahead *ex-ante* quarterly CFO predictions within the 2001-2005 prediction interval from equation (1) setting τ equal to 2. The use of two lags allows a relatively parsimonious estimation of equation (1).[5] We also generate CFO predictions from equation (2) that employs a lagged value for CFO in addition to six disaggregated accrual components. Unlike extant work on CFO prediction models, we estimate equations (1) and (2) *both* cross-sectionally and on a time-series basis. We estimated all cash-flow prediction models in a true *ex-ante* manner by not allowing future values of the respective independent variables in the holdout period (i.e., 2001-2005) to be used in parameter estimation. Instead, we employed random walk with drift projections of each independent variable which were then used to formulate n-step ahead CFO predictions. Finger (1994: 218) and Lorek and Willinger (1996: 92) provide additional discussion on this issue. In summary, we estimate four different statistically-based quarterly CFO prediction models and distinguish them by employing the following notation:

CS1-2lag = Equation (1) estimated cross-sectionally with τ = two lags.

CS2 = Equation (2) estimated cross-sectionally.

TS1-2lag = Equation (1) estimated on a time-series basis with τ = two lags.

TS2 = Equation (2) estimated on a time-series basis.

Finally, we assess the predictive ability of these quarterly CFO prediction models using both undeflated as well as deflated values of all variables to assess the sensitivity of the predictive findings across alternative CFO proxies.[6]

4.3 FIRM-SPECIFIC PARAMETERS

We present evidence on firm-specific variability of the parameters of Model TS1-2lag which is estimated on a time-series basis employing data in the model identification period (1989-2000). Recall that cross-sectional estimation procedures [i.e., the procedures used to estimate Models CS1-2lag and CS2 in the current study as well as all models estimated in Barth et al. (2001)] restrict parameter values to be constant across firms and time. Table 2 presents information on the variability of the coefficients of

Model TS1-2lag when CFOs are regressed upon current and past values of net earnings before extraordinary items using time-series estimation procedures. We observe that the mean, median, and quartile values for model coefficients evidence considerable variability across firms. Specifically, the mean (median) parameter value for current net earnings before extraordinary items is 1.03 (0.76), the first quartile value is 0.20 and the third quartile value is 1.80. Likewise, similar firm-specific variability is evidenced in the mean, median and quartile values of the other parameters (i.e., the first and second lagged values of net earnings before extraordinary items) as well as in the adjusted R^2 values. These descriptive findings are consistent with the notion that sample firms differ in their relationship between the dependent and independent variables employed in the quarterly CFO predictions models that we employ in a manner reminiscent of the discussion on cross-sectional estimation procedures by Neill et al. (1991), among others. Our predictive tests assess the impact, if any, of suppressing this inherent firm-specific variability via cross-sectional estimation versus allowing it to be reflected directly in the firm-specific parameter values via time-series estimation.

Table 2
Time-Series Variability of Parameters in the TS1-2lag Model Estimated on a Time-Series Basis

This table provides descriptive evidence on the extent of firm-specific variability in the coefficients of Model TS1-2Lag when CFO are regressed upon current and past values of net earnings before extraordinary items on a time-series basis. Model TS1-2Lag is based on Equation (1) in the text and is estimated on a time-series basis with $\tau = 2$ employing undeflated variables.

	Mean	Median	1st Quartile	3rd Quartile
Intercept	103.65	10.56	0.88	64.56
Current Earnings Parameter	1.03	0.76	0.20	1.80
Lag-One Earnings Parameter	0.20	0.27	-0.21	0.89
Lag-Two Earnings Parameter	0.34	0.15	-0.38	0.73
Adjusted R^2	23.74%	18.52%	4.60%	37.22%

4.4 RESEARCH HYPOTHESES

Neil et al. (1991) discuss the impact on predictive ability of restricting parameters to be constant across firms and time using cross-sectional estimation procedures. They suggest that cross-sectional estimation procedures may impede predictive performance if firms differ in their relationship between the dependent and independent variables in the regression model. Finally, they caution that with only one set of parameters estimated for all firms and all times the formulation of contextual firm-specific predictions is severely restricted. Since we provide descriptive evidence above documenting considerable firm-specific parameter variability when estimating the TS2 model, such descriptive behavior is consistent with firm-specific parameter differences and varying relationships between variables across sample firms. This implies that more contextual firm-specific expectations of CFO may be necessary to enhance predictive performance. If such parameter differences lead to differential predictive performance, CFO prediction models estimated on a time-series basis that capture such behavior should outperform models estimated cross-sectionally that simply ignore it. We test this notion empirically by initially employing relatively parsimonious CFO prediction models in order to concentrate upon the time-series versus cross-sectional impact on parameter estimation tested via predictive performance. This motivates the first research hypothesis:

Ho:1 Parsimonious quarterly cash-flow prediction models estimated on a time-series basis (TS1-2lag) exhibit superior predictive performance relative to parsimonious quarterly cash-flow prediction models estimated cross-sectionally (CS1-2lag).

Recall that Barth et al. (2001) provide descriptive goodness of fit results (i.e., adjusted R^2) that favor annual disaggregated accrual CFO prediction models (i.e., more complex models) versus the kind of models that we examine in Ho: 1, namely CFO prediction models that do not rely upon component data (i.e., parsimonious models). The disaggregated accrual models (i.e., CS2 and TS2) are considerably more complex since they employ independent variables for six major accrual components. To the extent that disaggregated accruals may capture firm-specific characteristics incrementally relative to aggregate net earnings, predictive ability may be enhanced. Whether such disaggregated accrual models are also differentially affected by how they are estimated (i.e., cross-sectionally or on a time-series basis) is the subject of our second research hypothesis. If the ability to estimate firm-specific parameters is also beneficial when estimating disaggregated accruals, then we would expect the predictive performance of TS2 to be superior to that evidenced by CS2. This leads to the second research hypothesis:

Ho: 2 Complex quarterly cash-flow prediction models (i.e., disaggregated accrual models) estimated on a time-series basis (TS2) exhibit superior predictive performance relative to complex quarterly cash-flow prediction models estimated cross-sectionally (CS2).

4.5 EVAULATIVE CRITERIA

We employ "out-of-sample" forecasts of one thru twenty step-ahead quarterly CFO. These forecasts are truly "ex-ante" in nature and are consistent with the setting faced by researchers and analysts who must generate multi-period-ahead quarterly CFO predictions in order to conduct firm valuations. We computed two error metrics: mean absolute deflated forecast error (MADFE) and mean absolute percentage error (MAPE) to assess predictive performance. The overall tenor of the results is not sensitive to the choice of error metric. We employ MADFE for expositional purposes when the CFO prediction models are estimated using undeflated variables and switch to the MAPE error metric when the CFO prediction models are estimated using deflated variables.[7] Forecast errors are defined as follows:

$$\text{MADFE} = 1 / n \ \Sigma \ | (A - F) / TA | \tag{3}$$

$$\text{MAPE} = 1 / n \ \Sigma \ | (A - F) / A | \tag{4}$$

where n= number of sample firms (n=296), A = actual CFOs for each sample firm in each quarter in the forecast horizon (2001-2005), F = forecasted CFO for each sample firm in each quarter, and TA = average total assets for each sample firm for each respective quarter in the forecast horizon.

5. *Predictive Results*

5.1 PREDICTIVE FINDINGS: LEVEL ANALYSIS

We generate one thru twenty step-ahead quarterly CFO predictions (i.e., all quarters within the 2001-2005 holdout period) estimating the parameters in the four CFO prediction models using data within the 1989-2000 identification period. Table 3 presents MADFE metrics for the CFO prediction models (i.e., Panel A: CS1-2lag and TS1-2lag tested in Ho:1; Panel B: CS2 and TS2 tested in Ho:2) for individual quarters (1st, 2nd, 3rd, and 4th), for all years within the holdout period (2001-2005), on a pooled basis across quarters and years where all CFO prediction models are estimated using undeflated values for the dependent and independent variables.

Table 3

Mean Absolute Deflated Errors: One-Thru Twenty Step-Ahead CFO Predictions Aggregated Across Quarters, Years, and Pooled

This table provides the MADFE values of the one thru twenty step-ahead quarterly CFO predictions across the prediction models tested in Ho:1 (i.e., CS1-2lag and TS1-2lag) and Ho:2 (i.e., CS2 and TS2) where all models are estimated using undeflated variables. Results are provided for individual quarters, years, and on a pooled basis across all quarters and years. Wilcoxon matched-pair comparisons are also provided for the pooled MADFE values.

	Quarters (n=1,480)				Years (n=1,184)					Pooled (n=5,920)
Panel A: (Ho:1)										
Model	**1**	**2**	**3**	**4**	**2001**	**2002**	**2003**	**2004**	**2005**	
CS1-2lag	.430	.416	.394	.396	.351	.416	.430	.426	.422	.409
TS1-2lag	.078	.068	.068	.080	.057	.071	.078	.080	.082	.074
Wilcoxon Matched-Pair Comparisons										.001
***W* Statistic**										56.91
Panel B: (Ho:2)										
Model	**1**	**2**	**3**	**4**	**2001**	**2002**	**2003**	**2004**	**2005**	
CS2	.142	.099	.088	.082	.114	.096	.102	.101	.101	.103
TS2	.101	.088	.080	.082	.064	.086	.095	.096	.096	.087
Wilcoxon Matched-Pair Comparisons										.001
***W* Statistic**										38.34

Where:

CS1-2lag = Equation (1) estimated cross-sectionally with τ = two lags.

CS2 = Equation (2) estimated cross-sectionally.

TS1-2lag = Equation (1) estimated on a time-series basis with τ = two lags.

TS2 = Equation (2) estimated on a time-series basis

The first research hypothesis assesses whether cross-sectional versus time-series estimation of the model parameters employed in parsimonious quarterly CFO prediction models significantly impacts predictive ability. Recall that the descriptive evidence presented in Table 2 is suggestive of considerable variability in such model parameters. This implies that CFO prediction models that rely upon time-series estimation which allows firm-specific parameter estimates may outperform CFO prediction models that rely upon cross-sectional estimation where parameters are held constant across firms and time effectively suppressing any firm-specific variability.

Panel A of Table 3 (Ho:1) provides all forecast errors across quarters, years, and on a pooled basis in addition to Wilcoxon matched-pair comparisons of the MADFE prediction errors associated with Models CS1-2lag versus TS1-2lag where method of parameter estimation (i.e., cross-sectional versus time-series) is allowed to vary. In general, we observe that the pooled MADFE value for the TS1-2lag model (.074) is significantly smaller (p=.001) than the pooled MADFE value for the CS1-2lag model (.409). The dominance of the TS1-2lag model is pervasive extending to all individual quarters and years in the holdout period. Specifically, untabulated matched-pair comparisons of these MADFE values reveal significantly superior predictive performance (p=.001) evidenced by the TS1-2lag model in each individual quarter and year. These results underscore the beneficial aspects of time-series versus cross-sectional estimation when parsimonious CFO quarterly prediction models are employed using undeflated variables for the independent and dependent variables in model estimation.

Panel B of Table 3 (Ho:2) provides all forecast errors across quarters, years, and on a pooled basis in addition to the Wilcoxon matched-pair comparisons of the relatively complex, quarterly CFO prediction models CS2 versus TS2, both of which are estimated using disaggregated accruals and undeflated variables. In general, we observe that the pooled MADFE value for the TS2 model (.087) is significantly smaller (p=.001) than the pooled MADFE value for the CS2 Model (.103). This suggests that the benefits of firm-specific parameter estimation employed in Model TS2 appear to outweigh the benefits of cross-sectional estimation when a host of disaggregated accruals is employed. Untabulated matched-pair comparisons of these MADFE values reveal the statistical dominance (p=.001) of the TS2 model for all years and quarters, with the singular exception of the 4th quarter forecast errors which are insignificantly different (p=.851). Similar to the results obtained in testing the parsimonious CFO prediction models in Ho:1 (CS1-2lag and TS1-2lag), the benefits of time-series versus cross-sectional estimation procedures are revealed. Finally, in untabulated results, we compared the accuracy of the predictions of the best parsimonious CFO prediction model in testing Ho:1 (TS1-2lag) versus the disaggregated accrual models employed in testing Ho:2 (CS2 and TS2) and found that the pooled predictions of the relatively parsimonious TS1-2lag model (.074) were significantly more accurate (p=.001) than the pooled predictions of either the relatively complex TS2 (.087) or CS2 (.103) models.

These empirical results suggest that relatively parsimonious CFO prediction models using aggregate data and estimated on a time-series basis (TS1-2lag) outperform both aggregate models estimated cross-sectionally (CS1-2lag) as well as more complex, disaggregated accrual models whether they are estimated cross-sectionally (CS2) or on a time-series basis (TS2). These findings should be of considerable interest to analysts and researchers who are interested in generating accurate multi-step ahead CFO projections. Whether such predictive findings pertain to CFO prediction models estimated using deflated variables is the subject of the next section.

5.2 PREDICTIVE FINDINGS: DEFLATED DATA

We present additional empirical analysis in this section where all CFO prediction models are estimated using deflated values for the dependent and independent variables.[8] Brown, Lo, and Lys (1999), among others, provide empirical evidence that use of undeflated variables in regression models where scale effects are present may result in an omitted correlated variable problem that results in biased regression coefficients and forecast errors. This problem is considerably more serious for cross-sectional regression models when sample firms of varying size are analyzed. Therefore, by re-estimating the CFO prediction models using deflated variables, we assess whether the dominance of time-series estimation reported earlier is simply an artifact of such scale effects.

Table 4
Mean Absolute Percentage Errors: One-Thru Twenty Step-Ahead CFO Predictions
Aggregated Across Quarters, Years, and Pooled

This table provides the MAPE values of the one thru twenty step-ahead quarterly CFO predictions across the prediction models tested in Ho:1 (i.e., CS1-2lag and TS1-2lag) and Ho:2 (i.e., CS2 and TS2) where all models are estimated using deflated variables. Results are provided for individual quarters, years, and on a pooled basis across all quarters and years. Wilcoxon matched-pair comparisons are provided for the pooled MAPE values.

	Quarters (n=1,480)				Years (n=1,184)					Pooled (n=5,920)
Panel A: (Ho:1)										
Model	**1**	**2**	**3**	**4**	**2001**	**2002**	**2003**	**2004**	**2005**	
CS1-2lag	.952	.836	.687	.541	.705	.733	.768	.778	.786	.754
TS1-2lag	.902	.742	.589	.528	.619	.672	.709	.722	.731	.690
Wilcoxon Matched-Pair Comparisons										.001
***W* Statistic**										23.89
Panel B: (Ho:2)										
Model	**1**	**2**	**3**	**4**	**2001**	**2002**	**2003**	**2004**	**2005**	
CS2	.950	.875	.741	.567	.731	.764	.794	.810	.818	.783
TS2	.916	.805	.662	.545	.635	.710	.747	.778	.788	.732
Wilcoxon Matched-Pair Comparisons										.001
***W* Statistic**										11.53

Where:

CS1-2lag = Equation (1) estimated cross-sectionally with τ = two lags.

CS2 = Equation (2) estimated cross-sectionally.

TS1-2lag = Equation (1) estimated on a time-series basis with τ = two lags.

TS2 = Equation (2) estimated on a time-series basis

Table 4 presents MAPE metrics for the CFO prediction models estimated using deflated variables across quarters, years, and on a pooled basis. We employ MAPE error metrics in this section to facilitate the exposition due to the mitigating effect of the "double deflation" process that is employed when MADFE error metrics are employed in conjunction with estimating the models using deflated variables. We emphasize that our results are qualitatively similar when the MADFE error metrics are employed. Panel A of Table 4 (Ho:1) compares the predictive ability of parsimonious CFO prediction models (CS1-2lag and TS1-2lag) allowing the method of parameter estimation (i.e., cross-sectional versus time-series) to vary. Similar to the undeflated analysis reported above, we observe that the pooled MAPE value for the TS1-2lag model (.690) is significantly smaller (p=.001) than the pooled MAPE value for the CS1-2lag model (.754). Untabulated matched-pair comparisons of the MAPE values across individual quarters and years reveals the significantly superior predictive performance (p=.001) of the TS1-2lag model in every comparison.

Panel B of Table 4 (Ho:2) compares predictive ability of the disaggregated accrual models estimated either cross-sectionally (CS2) or on a time-series basis (TS2) using deflated variables. Similar to the above results, we observe that the pooled MAPE value for the TS2 model (.732) is significantly smaller (p=.001) than the pooled MAPE value for the CS2 model (.783). Untabulated matched-pair comparisons of these MAPE values reveals the consistent statistical dominance (p=.001) of the TS2 model across all individual quarters and years. These results suggest that the benefits of time-series estimation procedures not only apply when undeflated variables are used to estimate the CFO prediction models, but also when deflated variables are employed. Finally, in untabulated results, we compared the best parsimonious CFO prediction model in testing Ho:1 (TS1-2lag) versus the disaggregated accrual models employed in testing Ho:2 (CS2 and TS2) and found that the pooled predictions of the TS1-2lag model (.690) were significantly more accurate (p=.001) than the pooled predictions of either TS2 (.732) or CS2 (.783). These findings underscore the pervasiveness of the dominance of time-series estimation vis-à-vis cross-sectional estimation in out-of-sample CFO predictions. We now expand the sample of firms considerably by dropping the stringent data requirements of the disaggregated accrual model in the next section.

6. *Expanded Sample*

Our previous empirical analysis has consistently demonstrated the superior predictive ability of parsimonious CFO prediction models using aggregate earnings data versus more complex, disaggregated accrual models. Since these latter models have considerable incremental data requirements (e.g., accounts receivable, accounts payable, inventory, depreciation, amortization, and other accruals all reported on a quarterly basis), we eliminated the component data requirements unique to such models thereby allowing us to test the predictive ability of the parsimonious CFO prediction models (CS1-2lag and TS1-2lag) across a significantly expanded sample of firms. Specifically, this increased sample size to 1,090 firms (i.e., 21,800 firm/quarter CFO predictions) from 296 firms (i.e., 5,920 firm/quarter CFO predictions) in the primary sample.

Table 5
Forecast Errors for Expanded Sample of 1,090 firms

This table provides error metrics (i.e., MADFE values in Panel A and MAPE values in Panel B) for the one thru twenty step-ahead quarterly CFO predictions using the expanded sample of firms (n=1,090). Results are provided for the parsimonious quarterly CFO prediction models (i.e., CS1-2lag and TS1-2lag) for individual quarters, years and on a pooled basis across all quarters and years. Wilcoxon matched-pair comparisons are provided for the respective pooled error metrics. Finally, the models are estimated using undeflated variables in Panel A and deflated variables in Panel B.

	Quarters (n=1,480)				Years (n=1,184)					Pooled (n=5,920)
Panel A: (Ho:1)										
Model	**1**	**2**	**3**	**4**	**2001**	**2002**	**2003**	**2004**	**2005**	
CS1-2lag	.387	.379	.334	.339	.349	.351	.366	.367	.365	.360
TS1-2lag	.080	.074	.077	.091	.065	.073	.084	.087	.092	.080
Wilcoxon Matched-Pair Comparisons										.001
***W* Statistic**										108.68
Panel B: (Ho:2)										
Model	**1**	**2**	**3**	**4**	**2001**	**2002**	**2003**	**2004**	**2005**	
CS1-2lag	.944	.834	.693	.562	.726	.726	.764	.784	.791	.758
TS1-2lag	.894	.731	.603	.556	.660	.665	.704	.715	.735	.696
Wilcoxon Matched-Pair Comparisons										.001
***W* Statistic**										22.65

Where:

CS1-2lag = Equation (1) estimated cross-sectionally with τ = two lags.

TS1-2lag = Equation (1) estimated on a time-series basis with τ = two lags.

Panel A of table 5 contains the MADFE forecast errors by quarter, year, and on a pooled basis for each of the parsimonious CFO prediction models estimated using undeflated variables. In essence, we are re-examining Ho:1 with considerably greater power given the expanded sample of firms. Once again, we observe that the pooled MADFE value for the TS1-2lag model (.080) is significantly smaller (p=.001) than the pooled MADFE value for the CS1-2lag model (.360). Untabulated matched-pair comparisons of these MADFE values reveal significantly superior predictive performance (p=.001) evidenced by the TS1-2lag model in each quarter and year in the holdout period.

Panel B of table 5 presents MAPE values for the same prediction models with the exception that each of the models was estimated using deflated values for all variables. Once again, however, the pooled MAPE value for the TS1-2lag model (.696) is significantly smaller (p=.001) than the pooled MAPE value for the CS1-2lag model (.758). With the exception of 4^{th} quarter results, untabulated matched-pair comparisons of these MAPE values reveal significantly superior predictive performance (p=.001) evidenced by the TS1-2lag model across all quarters and years.[9] These results enhance considerably the generalizability of our findings in support of the superior predictive ability of parsimonious CFO prediction models estimated on a time-series basis.

7. Concluding Remarks

The differential predictive ability of statistically-based, *quarterly* CFO prediction models has not been thoroughly examined using a true inter-temporal holdout period comprised of data not used in model estimation in the empirical, financial-based accounting literature despite the usefulness of such predictions to accounting researchers, standard setters, and financial analysts. We extend extant work on statistically-based, *annual* CFO prediction models (Dechow et al. 1998, Barth et al. 2001, and Kim and Kross, 2005) by examining the impact on predictive performance of using quarterly data and models. We assess the efficacy of two factors related to quarterly modeling: (1) time-series versus cross-sectional estimation procedures, and (2) use of parsimonious models that employ aggregate earnings data versus more complex, disaggregated accrual models.

Our empirical results consistently underscore the predictive superiority of quarterly CFO prediction models that are estimated on a time-series basis. Second, parsimonious models that employ aggregate earnings data are superior to more complex, disaggregated accrual models. Such results are consistent with the principle of parsimony wherein relatively complex prediction models that have impressive explanatory power may not perform well in true predictive settings using inter-temporal holdout periods containing data not used in model estimation. Moreover, the superior predictive performance of relatively parsimonious, time-series models is also consistent with the need to incorporate the firm-specific variability of parameters into expectations rather than restricting such parameters to be constant across firms and time when models are estimated cross-sectionally. Third, the above findings pertain to the set of quarterly CFO prediction models that we employ regardless of whether they are estimated using undeflated or deflated variables. Finally, these findings pertain to our primary sample of firms (n=296; 5,920 firm/quarter CFO predictions) as well as to an expanded sample of firms where we drop the stringent data requirements of the disaggregated accrual prediction models (n=1,090; 21,800 firm/quarter CFO predictions).

The aforementioned results provide a cautionary message to accounting researchers regarding a potential negative characteristic of cross-sectional estimation – as it pertains to quarterly CFO prediction models. Researchers are faced with an interesting set of tradeoffs when formulating methodologies incorporating quarterly CFO predictions which may need to be more fully examined in subsequent work. Specifically, are the potential benefits of incremental predictive performance using time-series estimation procedures of sufficient magnitude to warrant their usage vis-a-vis cross-sectional estimation? Such tradeoffs must factor into consideration the relatively smaller sample sizes that result when extensive time-series data requirements are invoked (relative to cross-sectional estimation) versus the enhanced predictive power that we document for the quarterly CFO prediction models that are estimated on a time-series basis. Definitive answers to such methodological questions may not be forthcoming; rather, they may be specific to the research designs and settings that employ quarterly CFO predictions. At a minimum, however, our empirical findings suggest that researchers need to assess the sensitivity of their results to using time-series versus cross-sectional estimation procedures for quarterly CFO prediction models.

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ENDNOTES

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[1] Possible explanations for the differences in our findings from Barth et al. (2001) include: 1) the so-called "regression fallacy" discussed by Kim and Kross (2005) and Watts and Leftwich (1977) wherein models that fit well descriptively do poorly in predicting future values, 2) Barth et al.'s use of cross-sectional estimation procedures as opposed to time-series estimation, and 3) our employment of a more recent holdout period (2001-2005) versus Barth et al's period of analysis that ended in 1996.

[2] Earlier work by Hopwood and McKeown (1992) and Lorek and Willinger (1996) used pre-SFAS No. 95 quarterly cash-flow data constructed via an algorithm. Stringent data requirements pertaining to quarterly earnings components severely limited sample size (e.g., 60 firms for Hopwood and McKeown and 51 to 61 firms for Lorek and Willinger depending on the predictive horizon that they examined) thereby reducing the external validity of such work.

[3] In essence, we invoke diffuse priors with respect to the optimal model structure for quarterly CFO. A reasonable starting point in this assessment is to simply extend the model structures developed upon annual data into the quarterly realm. For example, early work on the predictive ability of quarterly earnings data borrowed from models that were developed on annual earnings data (Lorek 1979, among others). An advantage of this strategy is the retention of the rich modeling theory employed in the development of annual cash flow prediction models. Formal statistical modeling of the seasonal patterns in quarterly CFO is an avenue to explore in future research.

[4] O'Brien (1988) and Dreman and Berry (1995), among others, provide empirical evidence that analysts tend to be overly optimistic in their earnings projections and fail to incorporate the time-series properties of earnings into their expectations. To the extent that such biases may also affect CFO projections, statistically-based forecasts of CFO provide a valuable alternative.

[5] As a partial control for any seasonal effects in the quarterly cash flow data, we allowed τ to vary to 6 which includes the seasonal lag of 4. In untabulated results, the predictive findings are qualitatively similar to those that we report in the text.

[6] See Brown, Lo, and Lys (1999) for a particularly lucid discussion of how use of undeflated variables may bias the parameters and/or forecast errors of regression models.

[7] While the results using MADFE for the CFO prediction models estimated using deflated variables are qualitatively similar to those that we report using the MAPE metric, the "double deflation" process (i.e., using deflated independent and dependent variables in model estimation as well as deflating the forecast errors by total assets) results in extremely small forecast errors that "tighten" the distribution of forecast errors across models thereby obscuring comparisons. For example, while the TS1-2lag model provides pooled MADFE values (.0013) that are significantly (p=.001) smaller than those of the CS1 model (.0021) and the TS2 model (.0019), the absolute value of the differences is mitigated due to the "double deflation" process. Therefore, the use of the MAPE metric in this setting is preferable from an expositional perspective.

[8] Specifically, each variable is deflated by dividing its value by average total assets for each sample firm for each respective quarter.

[9] The distinctive behavior of the 4th quarter CFO predictions is somewhat reminiscent of the "settling up" or "dumping" effect documented in 4th quarter EPS predictions by Bathke and Lorek (1984), among others.