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The Time-Series Properties of Quarterly Cash Flows

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I. INTRODUCTION

The predictability of quarterly cash flow from operations (CFO) is of considerable interest to standard-setting bodies, accounting researchers, and members of the investment community. Advances in the model structures of CFO prediction models (i.e., aggregate versus disaggregate-accrual models) by Dechow et al. (1998) and Barth et al. (2001) have led to refinements in the modeling of *annual* CFO data. Yet, advances in the modeling of *quarterly* CFO data have not been as forthcoming. In fact, the quarterly MULT CFO prediction model popularized more than a decade ago by Lorek and Willinger (1996) represents the most recent advancement in the structural modeling of quarterly CFO data. Dechow et al. (1998) speculate that the frequency of the measurement interval coupled with the presence of complex seasonal relationships mitigate against further advancements in quarterly CFO modeling. Nevertheless, the unavailability of widely disseminated analysts' quarterly CFO forecasts underscores the importance of continued refinements in the statistical modeling of quarterly CFO (see Barniv, Myring and Thomas 2005).¹

As an initial step in modeling quarterly CFO, the time-series properties of quarterly CFO need to be better specified.² Such work may provide initial clues on a host of modeling issues such as: (1) whether quarterly CFO exhibit quarter-to-quarter (adjacent) and/or quarter-by-quarter (seasonal) relationships, (2) whether consecutive and/or seasonal differencing is required to achieve stationarity, and (3) whether regular (seasonal) autoregressive and/or regular (seasonal) moving-average parameters need to be employed in a best-fitting ARIMA model for quarterly CFO, among other factors. Enough time has elapsed since the passage of SFAS No. 95 in 1988 such that a sufficiently long time series of reported quarterly CFO may be obtained for analyses similar to ours. Previously, proxy quarterly CFO series (PCFO) were constructed using simplistic algorithms (Bernard and Stober 1989; Lorek, Schaefer and Willinger 1993; Lorek and Willinger 1996, Dechow et al. 1998, among others) where non-cash expenses and certain changes in working capital were added/subtracted to earnings to derive the PCFO series. Hribar and Collins (2002), however, provide empirical evidence that PCFO differ significantly from reported CFO data. In fact, Kim and Kross (2005) suggest that CFOs reported under SFAS No. 95 are likely to be a less noisy measure than PCFOs. The purpose of this current paper, therefore, is to: (1) examine the time-series properties of reported quarterly CFO; (2) identify candidate cash-flow expectation models that are consistent with these properties, (3) assess their multi-step ahead predictability; and (4) determine the impact of accruals by comparing the parameters of best-fitting ARIMA models for quarterly CFO and quarterly earnings.

We provide new evidence pertaining to the predictability of statistically-based quarterly CFO prediction models emphasizing multi-step ahead extrapolations that are crucial to users interested in employing them in firm valuation settings (Palepu and Healy 2008 and Penman 2007, among others). We also employ methodological improvements such as: (1) estimating prediction models on a firm-specific time-series basis as opposed to estimating models cross-sectionally where all parameter values are necessarily the same for each sample firm; (2) employing an inter-temporal holdout period to assess predictive performance rather than relying exclusively upon in-sample descriptive goodness of fit measures; and (3) providing evidence on systematic differences between the parameter values of best-fitting ARIMA models for quarterly earnings and CFO.

The rest of the paper proceeds as follows. The next section details the motivation for the analysis followed by a literature review of salient empirical work assessing the predictability of CFOs. Next, we provide an explication of the research method including: (1) a discussion of the data acquisition procedures leading to the primary sample; (2) the identification of candidate expectation model(s) for quarterly CFO; and (3) the presentation of the predictive findings. Next, we provide a direct comparison of the time-series properties of quarterly CFO with the time-series properties of quarterly earnings by assessing whether estimated CFO and earnings parameter values differ systematically. Finally, we provide some concluding remarks and suggestions for future research.

II. MOTIVATION

The importance of cash-flow prediction has been a primary consideration to domestic and international standard-setting bodies in accounting for several decades. Recently, the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) issued a joint statement emphasizing that: "...an entity's investors and creditors (both present and potential) are directly interested in the amounts, timing, and uncertainty of their cash flows...." (IASB, FASB 2006, p. 18). Both professional bodies have clearly underscored the importance of fully understanding the linkages between accruals, cash-flow extrapolations, firm valuation, and financial reporting objectives. Consistent with this perspective, Barth (2006) emphasizes that CFO is a primitive valuation construct and that the aim of financial reporting is to aid financial statement users in predicting future CFO. Identification of the structural form of the best-fitting quarterly cash-flow prediction model should be of considerable interest to academic researchers interested in employing a proxy for the market's expectation of CFO in capital market research as well as to members of the investment community interested in formulating multi-step ahead cash-flow predictions that may serve as inputs to firm valuation methodologies.

Yoder (2007) emphasizes that a diverse set of firm-specific stakeholders are also interested in the predictability of CFO data. Specifically, potential suppliers to the firm are keenly interested in the firm's ability to generate future CFOs. Creditors must also assess the firm's cash-flow generating ability prior to lending or debt restructuring decisions. Finally, current and prospective employees are interested in whether the firm has the ability to meet projected payroll obligations. This widespread interest in the predictability of CFO underscores the importance of research efforts on refining cash-flow prediction models.

III. LITERATURE REVIEW

Dechow et al. (1998), Barth et al. (2001), Kim and Kross (2005), and Lorek and Willinger (2009), among others, have examined the predictability of *annual* CFO data.³ Yet, the structural modeling of annual CFO data does not provide insights regarding the time-series properties of *quarterly* CFO data due to the presence of seasonality inherent in interim data and the shorter measurement interval of the latter series, among other factors. Additional research is, therefore, necessary to model explicitly the adjacent lag structure (i.e., $t-1$, $t-2$, $t-3$, etc.) and/or seasonal relationships (i.e., $t-4$, $t-8$, $t-12$, etc.) of quarterly CFO. Earlier work by Lorek, Schaefer and Willinger (1993) and Lorek and Willinger (1996) provides evidence that quarterly CFO are highly seasonal but do not contain adjacent quarter-to-quarter autocorrelations. More recently, however, Lorek and Willinger (2008) present evidence that the time-series properties of quarterly CFO appear to be more complex consistent with a dual characterization containing *both* quarter-to-quarter adjacent relationships and quarter-by-quarter seasonal relationships.

Lorek, Schaefer and Willinger (1993) identified a seasonal autoregressive ARIMA model (SAR), a (000) X (100) model in Box-Jenkins ARIMA notation, that provided significantly more accurate *one-step ahead* quarterly CFO projections than the more complex, cross-sectionally estimated regression model of Wilson (1987) and Bernard and Stober (1989) during the 1985-1986 prediction interval. Barth et al. (2001) referred to Lorek et al.'s effort as a small-sample study since the sample size ranged from 66 to 80 firms depending upon the specific quarter in the forecast horizon. Lorek et al. derived a quarterly PCFO series wherein non-cash financial statement subcomponents were added back to net earnings since their time-series database ended a decade prior to the inception of the reporting requirements of SFAS No. 95. Whether such findings pertain to databases from more current time periods comprised of quarterly CFO data reported in accordance with SFAS No. 95 is an important issue.

Lorek and Willinger (1996) extended the aforementioned work by assessing the predictive performance of a multivariate time-series regression model (MULT) that employs three disaggregated accruals (i.e., receivables, payables, and inventory) as well as lagged values of CFO and operating

income. They provide justification for MULT across several dimensions: (1) It is a relatively parsimonious alternative to the very complex CFO prediction model employed by Wilson (1987) and Bernard and Stober (1989);⁴ (2) it employs lead/lag relationships between disaggregated accruals and CFO unlike the univariate SAR ARIMA model; and (3) it allows firm-specific estimation of parameters unlike the cross-sectional estimation procedures employed by Wilson (1987) and Bernard and Stober (1989). Lorek and Willinger demonstrate that the MULT model provided significantly more accurate *one-step ahead* quarterly CFO predictions than the SAR ARIMA model and several other more simplistic alternatives during the 1989-1991 prediction interval. It appears, however, that this study is subject to at least two external validity concerns. First, it employs quarterly PCFO data since its identification period (1979-1988) preceded the implementation of SFAS No. 95. Second, sample sizes ranged from 51 to 62 firms depending upon the specific quarter in the forecast horizon thus casting some doubt on the external validity of its findings.⁵

Recently, Lorek and Willinger (2008) examine the time-series properties and predictability of quarterly CFO data. They provide descriptive information that the time-series properties of quarterly CFO reported in accordance with SFAS No. 95 may be at variance with early works that had examined the quarterly PCFO series. Specifically, they provide empirical evidence that the time-series properties of quarterly CFO appear to be more complex than the quarterly PCFO series not only exhibiting seasonal quarter-by-quarter relationships but also adjacent quarter-to-quarter relations. They identify the (100) X (011) ARIMA model as a candidate cash-flow prediction model. This ARIMA model was originally popularized by Brown and Rozeff (1979), among others, as a candidate model for quarterly earnings-per-share. Lorek and Willinger (2008) provide evidence that the Brown-Rozeff ARIMA model significantly outperforms MULT and two naïve benchmark models (random walk with drift and seasonal random walk with drift) in *one-step* ahead predictions of quarterly CFO during the 2003-2005 prediction interval.

Unlike the prediction of quarterly earnings where ARIMA models were supplanted by predictions generated by sell-side analysts as the expectation model of choice, quarterly CFO forecasts attributed to analysts are not currently available on a widespread basis. Barniv, Myring and Thomas (2005) provide empirical evidence that analysts' CFO forecasts were only issued for 1% of their U. S. sample firms for which analysts' earnings forecasts were available. This suggests that statistically-based quarterly CFO forecasts currently represent the only widespread source of CFO expectational data. Evidence on quarterly CFO predictive ability provided by Lorek and Willinger (2008), however, is limited since CFO extrapolations were confined to *one-step* ahead predictions whereas researchers and analysts interested in firm valuations require multi-step ahead projections of CFO. We also provide a direct comparison of the

time-series properties exhibited in the quarterly CFO series vis-à-vis that exhibited by the quarterly earnings series. Such evidence on the similarities/dissimilarities between cash flows and accruals should help accounting researchers and standard setters better understand the linkages between accruals, cash flows and financial reporting objectives.

IV. RESEARCH METHOD

Sample Firms:

We obtained data from the quarterly Compustat industrial and research tapes from the first quarter, 1989 to the fourth quarter, 2007. Sample firms had calendar year-ends that met two sampling criteria: (1) They had a complete time series of quarterly CFO reported in accordance with SFAS No. 95 across the aforementioned interval, and (2) they had a complete time series of quarterly financial statement subcomponents necessary to operationalize MULT, the quarterly disaggregated-accrual CFO prediction model originally popularized by Lorek and Willinger (1996).⁶ These additional quarterly data items include operating income before depreciation, accounts receivable, inventory, and accounts payable. The primary sample consists of 192 firms that met the above data requirements.

Table 1
Two-Digit SIC Codes Represented in the Primary Sample

This table lists all seventeen two-digit SIC codes that have five or more firms represented in the primary sample of 192 firms. Additionally, there were 31 other two-digit SIC codes that were represented, each of them having fewer than five sample firms.

<u>SIC Code</u>	<u>Industry</u>	<u>Number of Firms</u>
28	Chemicals and Allied Products	22
36	Electronic and Other Electrical Equipment	14
73	Business Services	12
20	Food and Kindred Products	8
35	Machinery, Except Electrical	8
38	Instruments & Related Products	8
50	Wholesale Trade – Durable Goods	8
13	Oil & Gas Extraction	7
45	Transportation by Air	7
29	Petroleum and Coal Products	6
34	Fabricated Metal Products	6
49	Electric, Gas, and Sanitary Services	6
26	Paper and Allied Products	5
33	Primary Metal Industries	5
37	Transportation Equipment	5
48	Communications	5
63	Insurance Carriers	5
And 31 other 2-digit SIC Codes with less than 5 firms		<u>55</u>
Total Sample		192

Table 1 presents information on the concentration of sample firms across two-digit SIC codes. For example, the three industries with the greatest two-digit SIC code representation are: Chemicals and Allied Products (n=22, 11.5% of sample); Electronic and Other Electrical Equipment (n=14, 7.3% of sample); and Business Services (n=12, 6.3% of sample). Inspection of the remaining SIC codes and their sample representation reveals a wide dispersion of firms across industries.

Inter-temporal Forecast Horizon:

Unlike Barth et al. (2001), among others, we employ a model identification period (56 quarters within the 1989 to 2002 interval) and a separate inter-temporal holdout period containing data not employed in model identification (20 quarters within the 2003-2007 interval). Watts and Leftwich (1977) discuss the methodological advantages of employing out-of-sample predictive assessments vis-à-vis using in-sample descriptive goodness of fit measures to assess predictive ability. Sole reliance upon descriptive performance may be subject to the descriptive-predictive paradox where models that fit well in the identification period may not predict accurately in the future due to data overfitting and/or model complexity.

Another important methodological consideration is the length of the forecast horizon. As Brown and Rozeff (1979: 183-4) suggest one-step ahead evaluations of predictive performance like those reported in Lorek and Willinger (2008), among others, are only sufficient if the expectation models yield different forecasts *and* such differences persist across all forecast horizons. Whether these restrictive conditions are met in the current setting is problematic. Inspection of the forecast function of the Brown-Rozeff (BR) ARIMA model reveals a quite different forecast profile than the MULT model due to at least two factors. First, the lag structure of the independent variables in the BR ARIMA model is more complicated than that in MULT. Specifically, it includes a seasonally-lagged value of CFO (i.e., CFO_{t-4}), a one-period removed seasonal difference of CFO [i.e., $(CFO_{t-1} - CFO_{t-5})$], and a disturbance term formulated from the error in predicting CFO four quarters prior (i.e., a_{t-4}). Second, the MULT model's use of lagged balance sheet and operating income variables (i.e., AR_{t-1} , INV_{t-1} , AP_{t-1} , $OIBD_{t-1}$, and $OIBD_{t-4}$) differs substantially from the univariate nature of the BR ARIMA model. Recall that the latter prediction model only considers independent variables that are lagged values of the dependent variable (i.e., CFO_{t-1} , CFO_{t-2} , CFO_{t-n}). Therefore, Lorek and Willinger's finding that the Brown-Rozeff model's predictions of one-step ahead CFO are significantly more accurate than the one-step ahead CFO predictions of MULT may or may not pertain to longer-term forecast horizons. At a minimum, this is an important issue that needs to be resolved empirically.

We observe that a considerable number of other cash-flow prediction studies have also limited the prediction of future CFOs to one-step-ahead (e.g., Lorek, Schaefer, and Willinger 1993, Lorek and Willinger 1996, and Kim and Kross, 2005, among others). Since sell-side analysts and investors need multi-step ahead CFO predictions to operationalize firm valuation methodologies like discounted cash flows, results from these studies are not particularly useful to them in their attempt to find a best-performing multi-step ahead CFO prediction model. Therefore, we assess the accuracy of one thru twenty step-ahead predictions of quarterly CFO to more fully evaluate the predictive performance of candidate quarterly CFO expectation models.⁷

Time-series Estimation:

We test quarterly CFO prediction models that estimate parameters on a firm-specific, time-series basis as opposed to cross-sectionally. Each estimation procedure has comparative advantages. While studies like ours that invoke time-series estimation typically examine smaller samples of firms due to relatively onerous data constraints, they benefit from the ability to capture firm-specific, contextual relationships. In fact, Lorek and Willinger (2009) provide salient empirical evidence that the beta parameter in an annual CFO prediction model that regresses CFO upon net earnings exhibits considerable firm-specific variability. The quarterly CFO prediction models that we examine are able to track firm-specific components whereas cross-sectional estimation constrains all parameter values to be constant across firms and time. Neill et al. (1991) provide a particularly lucid discussion on the impact of restricting parameter values in this manner.

Prediction Models:

We initially assess the long-term predictive power (i.e., one thru twenty steps-ahead) of two quarterly cash-flow prediction models that have empirical support in the literature based exclusively on their demonstrated short-term predictive power (i.e., one step-ahead). Lorek and Willinger (1996) provide evidence supportive of the first model, a disaggregated-accrual, multivariate time-series regression model (MULT) stipulated below:

$$\text{CFO}_t = a + b_1 (\text{CFO}_{t-1}) + b_2 (\text{CFO}_{t-4}) + b_3 (\text{OIBD}_{t-1}) + b_4 (\text{OIBD}_{t-4}) + b_5 (\text{REC}_{t-1}) + b_6 (\text{INV}_{t-1}) + b_7 (\text{PAY}_{t-1}) + e_t \quad (1)$$

where: CFO_t = operating cash flows at time t

OIBD_{t-i} = operating income before depreciation at time t-i

REC_{t-1} = accounts receivable at time t-1

INV_{t-1} = inventory at time t-1

PAY_{t-1} = accounts payable at time t-1

e_t = current disturbance term.

The MULT model employs lagged values of CFO, operating income, receivables, payables, and inventory while also allowing firm-specific parameter estimation. While Lorek and Willinger (1996) provide evidence that it dominates a host of ARIMA-based models in short-term predictive performance of CFO, Lorek and Willinger (2008) provide evidence that the ARIMA model described below provides superior short-term predictive power in more recent time periods. Therefore, the second quarterly cash-flow prediction model that we examine is the BR ARIMA model, (100) X (011) in Box-Jenkins notation. It was originally developed by Brown and Rozeff (1979) as a candidate prediction model for quarterly earnings per share. The BR ARIMA model is very parsimonious in nature only relying upon lagged values of the quarterly CFO series to derive its model structure. This is in sharp contrast to the host of variables employed in the MULT model. The BR ARIMA model may be stipulated as follows:

$$CFO_t = CFO_{t-4} + \phi_1 (CFO_{t-1} - CFO_{t-5}) + a_t - \Theta_1 (a_{t-4}) \quad (2)$$

where: CFO_t = operating cash flows at time t

ϕ_1 = autoregressive parameter

Θ_1 =seasonal moving-average parameter

a_t = current disturbance term

V. PREDICTIVE PERFORMANCE

We generated one-thru-twenty step-ahead quarterly CFO predictions using the two cash-flow prediction models discussed above. The models employed an identification and estimation database employing 10,752 firm/quarter observations (i.e., 192 x 56) that begins with the first quarter of 1989 and ends with the fourth quarter of 2002. The forecast holdout period was comprised of the twenty quarters in the 2003-2007 time interval. This yielded 3,840 firm/quarter CFO predictions (i.e., 192 x 20) for the primary sample of firms. We employed two error metrics to assess the long-term predictive power of the MULT and BR ARIMA models. Mean absolute percentage error (MAPE) served as the primary error metric which is stipulated below:

$$MAPE = 1/n \sum | (A - F) / A | \quad (3)$$

where, n = number of predictions; A = actual quarterly CFOs; and F = forecasted quarterly CFOs. All forecast errors greater than 100% were truncated to 100% to avoid the effects of explosive forecast errors. We also employed mean absolute deflated forecast errors where the denominator in equation (3) was replaced by average total assets for each sample firm. Since the overall tenor of the results was unaffected by the choice of error metric, we use MAPE for exposition purposes.

Table 2 presents the MAPE error metrics for the one-thru-twenty step-ahead quarterly CFO predictions for the BR ARIMA and MULT cash-flow prediction models across quarters (1st, 2nd, 3rd, 4th), years (2003, 2004, 2005, 2006, 2007), and on a pooled basis across all quarters and years. We report new empirical evidence that the short-term predictive dominance of the BR ARIMA model reported by Lorek and Willinger (2008) also extends to longer-term predictions. Specifically, the BR ARIMA model has a pooled MAPE of .630 versus .788 for the MULT model. This predictive dominance appears pervasive with the BR ARIMA model providing more accurate CFO forecasts in each individual quarter and year in the holdout period. Table 2 also indicates that each of the pairwise comparisons between the prediction models (i.e., by quarter, year, and pooled) is statistically significant ($p = .001$) using the Wilcoxon rank-sum test. Therefore, researchers and analysts interested in generating multi step-ahead quarterly CFO forecasts should consider adopting the BR ARIMA model's structure versus MULT, the disaggregated accrual, time-series regression model. These results are consistent with Occam's razor and the principle of parsimony which suggests that relatively simpler univariate models, like the BR ARIMA model, may outperform more complex models, like MULT due to possible data overfitting as well as structural changes between CFO and the independent variables in the holdout period.

Table 2
Mean Absolute Percent Errors of One Thru Twenty Step-Ahead Quarterly CFO Predictions
Primary Sample (n=192 firms)

This table contains MAPE error metrics associated with one-thru-twenty step-ahead quarterly CFO predictions from the Brown-Rozeff ARIMA model and the disaggregated accrual, time-series regression model, MULT. MAPEs are displayed across quarters, years, and pooled across quarters and years in the holdout period. Wilcoxon rank sum statistical tests assess the significance of the differences between each of the respective error metrics. Forecasts are generated for 3,840 firm/quarter predictions (i.e., 192 firms x 20 steps-ahead).

<u>Model</u>	<u>Quarter</u>				<u>Year</u>					<u>Pooled</u>
	1 st	2 nd	3 rd	4 th	2003	2004	2005	2006	2007	
BR ARIMA	.688	.611	.601	.620	.578	.616	.636	.656	.664	.630
MULT	.828	.799	.777	.750	.767	.782	.803	.805	.785	.788
Wilcoxon Z-Score	9.56	12.70	12.12	9.60	11.46	10.41	10.27	9.70	7.61	22.14
Significance Level	.001	.001	.001	.001	.001	.001	.001	.001	.001	.001

where:

BR = The (100) X (011) Brown-Rozeff ARIMA model

MULT = The disaggregated accrual, time-series regression model

Due to the dominant predictive performance of the BR ARIMA model (at least relative to MULT), we decided to drop MULT's stringent data requirements with respect to disaggregated accruals which allowed expansion of the sample to 722 firms. This enabled us to assess whether there might be other parsimonious ARIMA model structures that might be identified on the basis of the time-series behavior of quarterly CFO exhibited in the sample autocorrelation functions (SACFs) and partial autocorrelation functions (PACFs) of the expanded sample of firms during the model identification period, 1989 to 2002. Table 3 provides the cross-sectionally derived SACF and PACF functions for the undifferenced as well as the consecutively and seasonally differenced quarterly CFO series.⁸ Specifically, SACF (PACF) values were computed for each sample firm beginning with the first quarter, 1989 and ending with the fourth quarter of 2002 using a methodology similar to Lorek and Willinger (2008),

among others. In essence, firm-specific SACF (PACF) values are summed across sample firms and averaged to obtain the values reported across the twelve lags displayed in table 3. Each of these series led to the identification of a competing parsimonious ARIMA model to the BR ARIMA model.

Table 3

**Cross-sectional Sample Autocorrelation Function: 1989-2002
Expanded Sample (n=722)**

This table provides cross-sectionally derived SACF and PACF functions of the undifferenced (panel A) as well as consecutively and seasonally differenced (panel B) quarterly CFO series. We computed SACF values for all twelve lags for each sample firm over 56 quarterly CFO observations beginning with the first quarter, 1989 and ending with the last observation in the identification period, the fourth quarter of 2002.

Panel A: Undifferenced Data: (Means and Standard Deviations)

	Lags											
	1	2	3	4	5	6	7	8	9	10	11	12
SACF	.138 (.315)	.152 (.306)	.110 (.262)	.345 (.263)	.078 (.232)	.070 (.242)	.048 (.209)	.243 (.228)	.029 (.178)	.023 (.192)	.022 (.159)	.170 (.198)
PACF	.138 (.315)	.054 (.248)	.024 (.201)	.226 (.235)	-.028 (.147)	-.041 (.133)	-.013 (.124)	.057 (.131)	-.024 (.115)	-.030 (.110)	-.007 (.111)	.011 (.111)

Panel B: Consecutively and Seasonally-Differenced Data: (Means and Standard Deviations)

	Lags											
	1	2	3	4	5	6	7	8	9	10	11	12
SACF	-.456 (.155)	.015 (.130)	.181 (.171)	-.390 (.151)	.174 (.170)	-.003 (.177)	.004 (.174)	-.011 (.173)	.002 (.162)	.001 (.158)	.011 (.160)	-.006 (.149)
PACF	-.456 (.155)	-.300 (.174)	.077 (.135)	-.335 (.149)	-.201 (.133)	-.159 (.143)	.041 (.128)	-.174 (.138)	-.112 (.115)	-.096 (.122)	.032 (.114)	-.095 (.118)

Where:

SACF = sample autocorrelation function

PACF = partial autocorrelation function

SACF (PACF) values in panel A of table 3, the undifferenced quarterly CFO series, reveal seasonal autoregressive behavior consistent with the (000) X (100) seasonal autoregressive (SAR) ARIMA model originally popularized as a candidate expectation model for quarterly PCFO by Lorek, Schaefer, and Willinger (1993). Specifically, SACF values decline markedly at lags four, eight, and twelve (.345, .243, and .170) and the PACF value cuts off after the first lag (.138) consistent with a seasonal autoregressive parameter. Other lags exhibit autocorrelation consistent with a white-noise series thus leading to the identification of the SAR ARIMA model. We then assessed the comparative predictive performance of the SAR and BR ARIMA models on the expanded sample of firms yielding 14,440 firm/quarter predictions (i.e., 722 firms x 20 quarters). Untabulated MAPE metrics reveal a pooled MAPE of .643 for the SAR ARIMA model versus .612 for the BR ARIMA model. Wilcoxon rank-sum statistics reveal that the BR ARIMA model's predictions were significantly ($p = .001$) more accurate than those of the SAR ARIMA model in each quarter, year, and on a pooled basis in the holdout period.

Further inspection of the SACF (PACF) patterns in panel B of table 3 (the consecutively and seasonally-differenced series) reveals spikes at the first lag (-.456) and the fourth lag (-.390) with insignificant autocorrelation at the remaining lags of the SACF. Such behavior is consistent with the (011) X (011) parsimonious ARIMA process, originally identified by Griffin (1977), among others, as being descriptive of the quarterly earnings series. Comparing predictive performance, untabulated MAPE metrics reveal a pooled MAPE value of .709 for the (011) X (011) ARIMA model, which is significantly ($p = .001$) greater than the .612 value for the BR ARIMA model. Therefore, these competing parsimonious ARIMA models are unable to outperform the BR ARIMA model in one-thru-twenty step-ahead quarterly CFO predictions. This expanded sample analysis has increased confidence in the propriety of the BR ARIMA model as an expectation model for quarterly CFO data.

VI. SUPPLEMENTARY ANALYSIS

We now compare certain aspects of the time-series properties of quarterly earnings and quarterly CFO by examining the respective autoregressive (AR1) and seasonal moving-average (SMA4) parameter values for each series estimated via the common structure of the BR ARIMA model. We observe that Brown and Rozeff (1979) and Bathke and Lorek (1984), among others, provide descriptive and predictive evidence supportive of the BR (100) X (011) ARIMA structure for quarterly earnings. Untabulated SACF (PACF) analysis of 671 firms with complete quarterly earnings data during the model identification period from 1989 to 2002 (out of the 722 firm expanded sample) reinforces the propriety of the BR ARIMA structure on more recent quarterly earnings time-series data.

The historical cost model employs both short-term and long-term accruals that induce serial correlation on the time series of quarterly earnings vis-a-vis quarterly CFO.⁹ For example, Lifo/Fifo inventory flow assumptions and straight-line or accelerated methods of depreciation allocate expenses to successive quarters using mechanical rubrics that induce consistent patterns in quarter-to-quarter earnings numbers that are not present – at least to the same degree – in quarter-to-quarter CFO series. Although *both* series exhibit time-series properties consistent with the BR (100) X (011) ARIMA structure, we hypothesize that the accrual process may induce incremental serial correlation in the quarterly earnings series vis-a-vis the quarterly CFO series leading to the estimation of systematically greater AR1 and SMA4 parameter values.

Table 4 provides mean values for the AR1 and SMA4 parameters for the BR ARIMA model estimated using data from the model identification period: 1989-2002. Consistent with our priors, the AR1 (SMA4) mean values are greater for earnings versus CFO. Specifically, the Mann-Whitney U-test reports that the AR1 parameter is significantly greater ($p=.001$) for earnings (.366) than CFO (.109). Similarly, the SMA4 parameter is significantly greater ($p=.001$) for earnings (.635) than CFO (.578). These findings are consistent with the accrual accounting process inducing incremental serial correlation in the quarterly earnings series relative to the quarterly CFO series. Although both series share common inputs such that the structures of best-performing statistically-based ARIMA models for quarterly earnings and quarterly CFO are identical, systematic differences in parameter values are observed. This finding may help standard setters better understand the empirical linkages between earnings and CFO. That is, specific knowledge regarding the extent to which the accrual process alters the statistical properties of the quarterly earnings series relative to the more primitive quarterly CFO series may help standard setters understand better the linkages between CFO, earnings and valuation.

Table 4

**Comparison of Parameters in the Brown-Rozeff ARIMA Model for Quarterly Earnings
and Quarterly CFO
Model Identification Period: 1989-2002**

This table compares the regular autoregressive parameters (AR1) and seasonal moving-average parameters (SMA4) of the Brown-Rozeff (100) X (011) ARIMA model estimated for both quarterly earnings and quarterly CFO across the 56 quarters in the model identification period: 1989-2002.

<u>Series</u>	<u>Mean AR1 Parameter</u>	<u>Mean SMA4 Parameter</u>
Quarterly Earnings (n=671)	.366	.635
Quarterly CFO (n=722)	.109	.578
Chi-Square	246.63	39.62
Significance Level	.001	.001

Where: AR1 = regular autoregressive parameter at lag one
SMA4 = seasonal moving-average parameter at lag four

VII. CONCLUDING REMARKS

We provide new empirical results supportive of the parsimonious BR (100) X (011) ARIMA model as a candidate statistically-based, multi-period ahead prediction model for quarterly CFO. This evidence should be of interest to standard-setting bodies in accounting as they further explicate the linkages between accruals, cash-flow extrapolations, and financial reporting objectives, members of the investment community interested in formulating multi-step ahead cash-flow predictions that may serve as inputs to firm valuation methodologies, and accounting researchers interested in developing statistical proxies for the market's expectations of multi-step ahead quarterly CFO.

While considerable refinements in the structural modeling of annual CFO data have been reported by Dechow et al. (1998) and Barth et al. (2001), among others, relatively recent advancements in the modeling of quarterly CFO have not been as forthcoming. Our empirical findings suggest: (1) The structural form of statistically-based quarterly CFO prediction models appears similar to that employed for quarterly earnings, namely the BR (100) X (011) ARIMA model; (2) the inter-temporal multi-step ahead predictive power of the time-series regression model (MULT) popularized by Lorek and Willinger (1996) is lacking perhaps due, among other factors, to either the use of a proxy cash-flow series and/or the relatively small sample sizes that they tested; (3) the dominance of the BR ARIMA model is pervasive extending to all quarters, years, and pooled periods in the 2003-2007 inter-temporal holdout period that we employ; and (4) consistent with our priors, the common-structure ARIMA model for quarterly earnings and CFO (i.e., the BR ARIMA model) exhibits systematically greater AR1 and SMA4 parameter values for earnings vis-à-vis CFO. These findings underscore a considerably more complicated pattern of autocorrelation in quarterly CFO data reported in accordance with SFAS No. 95 than earlier work employing proxy series. Further advancements in the structural modeling of quarterly CFO need to factor in the adjacent and seasonal lag structure of the Brown-Rozeff ARIMA model when specifying lead/lag relationships between dependent and independent variables. Nevertheless, it may be very difficult to construct more complicated, statistically-based regression models that outperform the relatively parsimonious ARIMA models tested herein due to the effects of Occam's razor and the principle of parsimony that we document.

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ENDNOTES

¹ It is interesting to speculate upon why so few analysts provide quarterly CFO forecasts. Possible reasons include: (1) the increased variability of CFO vis-à-vis earnings making it more difficult to forecast accurately, (2) possible loss of reputation if CFO predictions are not realized, and/or (3) the primacy of EPS versus CFO in the financial press.

² In an unpublished working paper, Brochet, Nam and Ronen (2008) pursue an alternative strategy. They assess the predictive ability of a set of time-series regression models that employ quarterly cash flow from operations, quarterly free cash flows, and market value of equity as separate objects of prediction. Instead of modeling seasonality explicitly via the ARIMA methodology, they deflate all variables by total assets and deseasonalize them using the X-11 methodology. Due to such transformations, their objects of prediction, unlike ours, may not be of direct interest to financial analysts seeking CFO extrapolations necessary for firm valuation.

³ Both Cheng and Hollie (2008) and Luo (2008) also examine annual CFO prediction models. Cheng and Hollie extend Barth et al.'s CFO prediction model by decomposing CFO into its core and non-core subcomponents. They find that such subcomponents are differentially useful in predicting future CFO values. Luo hand collects unusual firm-specific cash flow items generated from significant or unusual transactions and shows that such items are also associated with future CFO values. Since both studies estimate their models cross-sectionally and rely exclusively upon descriptive goodness of fit measures to assess predictive performance, they are not directly related to the current paper. Finally, Yoder (2007) extends the Barth et al. annual CFO prediction model by including cash flow implications of growth in future sales.

⁴ Parsimony is a relative concept. For example, the MULT model is considerably more parsimonious than the cross-sectional model employed by Wilson (1987) and Bernard and Stober (1989) since MULT only employs a set of 7 independent variables as opposed to 15 independent variables employed in the latter works. Yet, The Brown-Rozeff ARIMA model is more parsimonious than MULT since it is a univariate model employing only lagged values of CFO as potential independent variables.

⁵ Another work that may be subject to the aforementioned limitations is Hopwood and McKeown (1992).

⁶ We also tested non-calendar year-end firms separately: 1/31 (n=52); 3/31 (n=64); 6/30 (n=53) and 9/30 (n=93) with qualitatively similar predictive findings to those reported in the next section of the paper.

⁷ Lundholm and Sloan (2007), Palepu and Healy (2008), and Penman (2007) underscore the need for multi year-ahead CFO forecasts as inputs to firm valuation.

⁸ No additional modeling insights were derived from inspection of the consecutively-differenced or seasonally-differenced SACF (PACF) values.

⁹ Beaver (1970) provides an insightful discussion on precisely how accounting conventions like inventory flow assumptions and/or depreciation methods impact the time-series properties of earnings.