NORTHERN ARIZONA UNIVERSITY
College of Business Administration

Time-Series Properties and Predictive Ability of Quarterly Cash Flows

Working Paper Series—06-10 | November 2006

Kenneth S. Lorek*

and

G. Lee Willinger**

* Corresponding Author
College of Business Administration
PO Box 15066
Northern Arizona University
Flagstaff, AZ 86011-5066
Telephone: (928) 523-7406
e-mail: Ken.Lorek@nau.edu
fax: (928) 523-7331

** Price College of Business
University of Oklahoma
Norman, Ok 73019
Telephone: (405) 325-5780
e-mail: lwilling@ou.edu

Time-Series Properties and Predictive Ability of Quarterly Cash Flows

Kenneth S. Lorek and G. Lee Willinger

I. Introduction

We examine the time-series properties and predictive ability of *quarterly* cash flows from operations (CFO) reported in accordance with Statement of Financial Accounting Standards (SFAS) No. 95. Previous empirical work on *quarterly* CFO has relied exclusively upon proxies for the CFO series (PCFO) computed using relatively simplistic algorithms that employ a diverse set of subcomponents from quarterly financial statements. This approach had been necessary due to the previous unavailability of a sufficiently long time series of reported CFO since FASB Standard No. 95 only required firms to present a statement of cash flows for fiscal years ending after July 15, 1988 (FASB 1987).

Hopwood and McKeown (1992) and Lorek and Willinger (1996) (LW), among others, analyzed the time-series properties and predictive ability of quarterly PCFO. Unfortunately, these works have been characterized as small-sample studies (i.e., 60 firms for Hopwood and McKeown and 51 to 62 firms for LW depending on the predictive horizon that they examined) due to demanding data requirements pertaining to a diverse set of quarterly financial statement subcomponents necessary to construct the PCFO series. The external validity of these studies is compromised from at least two perspectives: 1) quarterly PCFO series constructed using relatively simplistic algorithms may exhibit different time-series properties than quarterly CFO reported under more comprehensive SFAS No. 95 requirements, and 2) small-sample studies mitigate against generalizability across a wider set of firms. Kim and Kross (2005) suggest that CFOs reported under the auspices of SFAS No. 95 are likely to be a less noisy measure than proxies computed using relatively simplistic algorithms. Therefore, additional research is necessary to determine the robustness of extant descriptive and predictive findings that pertain solely to the quarterly PCFO series.

The objectives of the current paper are twofold: 1) to provide new empirical evidence on the time-series properties of quarterly CFO reported in accordance with SFAS No. 95, and 2) to assess the predictive performance of a set of quarterly CFO prediction models. SFAS No. 95 has been in place a sufficiently long time period such that a time series of quarterly CFO is now available for analysis (i.e., 1st quarter, 1989 to 4th quarter, 2005 in the current study). We are unaware of any previous empirical work that has examined the time-series properties of quarterly CFO.

Analysis of sample autocorrelation functions (SACFs) of PCFO data in LSW, among others, has revealed idiosyncratic time-series behavior that is purely seasonal in nature (i.e., quarter-by-quarter) with virtually no adjacent (i.e., quarter-to-quarter) autocorrelation. This descriptive evidence led Lorek, Schaefer and Willinger (1993) (LSW) to identify quarterly ARIMA prediction models [e.g., (000) x (100) a seasonal autoregressive model and (000) x (011) seasonal moving average model] that employ *seasonal* autoregressive and/or *seasonal* moving-average parameters.[1] A criticism of these ARIMA models is that they lack economic intuition in the sense that they generate cash-flow predictions based entirely upon relatively stale, seasonal information at least four quarters old ignoring more current information from one, two, and three-quarters ago.

Our findings contribute to the quarterly cash-flow prediction literature across several important dimensions. First, we present new descriptive evidence based on analysis of SACFs indicating that the time-series properties of quarterly CFO reported in accordance with SFAS No. 95 are at variance with the exclusively seasonal characterization of quarterly PCFO generated using relatively simplistic algorithms. Quarterly CFO exhibit both adjacent (quarter-to-quarter) *and* seasonal (quarter-by-quarter) relationships unlike the exclusively seasonal time-series properties documented for the quarterly PCFO series. This more complex pattern of autocorrelation is reminiscent of the time-series properties of quarterly earnings documented in the literature (Foster 1977, among others). Second, we identify the (100) x (011) Brown-Rozeff (1979) ARIMA model (BR) as a candidate expectation model for reported quarterly CFO and provide predictive evidence supportive of this cash-flow prediction model. The BR model significantly outperforms a multivariate time-series regression model (MULT) popularized originally by LW as well as quarterly random walk with drift (RWD) and seasonal random walk with drift (SRWD) benchmark models.[2] Third, we also provide new evidence that the forecast errors of larger firms are significantly smaller than the forecast errors of smaller firms. Finally, we assess the robustness of the predictive ability of the BR ARIMA model on an expanded sample of firms (n=745) obtained by deleting the considerable data requirements necessary to estimate MULT. These supplementary findings undersore the robustness of the predictive power of the BR model.

The remainder of the paper is organized as follows. Section II relates the study to extant work and serves to motivate our analysis. Section III describes the sample and presents descriptive findings with respect to the time-series properties of CFO. Section IV discusses the quarterly CFO prediction models that we employ. Section V presents the primary predictive findings. Section VI presents results from additional analyses. Finally, section VII provides concluding remarks.

II. Relation to Prior Research

Prediction of CFO is an important task relevant to a host of economic decisions ranging from valuation methodologies employing discounted cash flows, distress prediction, risk assessment, and the provision of value-relevant information to security markets.[3] Kim and Kross (2005) observe that theoretical valuation models favor the use of CFO as an input series versus net earnings. Standard setting bodies have also emphasized that prediction of CFO provides an underlying rationale for the existence of accrual accounting. SFAC No. 1 (FASB 1978, par. 37) states that the primary objective of financial reporting is to: "…provide information to help investors, creditors, and others assess the amounts, timing, and uncertainty of prospective net cash inflows to the related enterprise." This provides motivation to examine the time-series properties and predictive ability of reported CFO rather than simply relying upon the descriptive and predictive evidence provided to date on the quarterly PCFO series, a proxy that previous researchers employed due to the unavailability of sufficiently long time series of quarterly CFO.

Considerable work has been devoted to assessing the predictive ability of *annual* CFO. Dechow et al. (1998), Barth et al. (2001), and Kim and Kross (2005), among others, have examined the predictive ability of annual cash-flow models. A potential advantage of annual work is the ability to obtain relatively large samples of firms that meet data requirements. A potential disadvantage, however, is that annual work typically employs relatively short data bases in an effort to mitigate structural change problems, precluding rigorous SACF analysis. In fact, the purely seasonal characteristics of quarterly PCFO documented by LSW, among others, are aggregated and eliminated in annual data, masking a potentially important source of autocorrelation.[4]

Far less research has been conducted on quarterly CFO series due to the relatively stringent data requirements associated with algorithms that rely upon subcomponents of quarterly financial statements. For example, Hopwood and McKeown (1992) started with operating income before depreciation, added the increase in total current liabilities, and subtracted the increase in total current assets minus the increase in cash to derive quarterly PCFO. LW, on the other hand, subtracted interest expense, the current portion of income tax expense, and the increase in net working capital (other than cash and securities) from operating income before depreciation to derive their quarterly PCFO series. Such algorithms, however, necessarily avoid more complex transactions and events in order to maintain adequate sample size. Mulford and Comiskey (2002: 345-78) discuss numerous items that are included in the cash-flow statement in accordance with the reporting requirements of SFAS No. 95, but are *not* considered by the simplistic algorithms. These include the cumulative effect of changes in accounting principles, income taxes on transactions classified as investing or financing activities, tax benefits of nonqualified employee stock options, and unrealized foreign-currency gains and losses. The financial complexities and nuances of such items may cause the time-series properties of quarterly CFO to differ systematically from the quarterly PCFO series since the former series includes such items while the latter series does not. We provide descriptive evidence on whether the time-series properties of quarterly CFO series differ systematically from the time-series properties of quarterly PCFO previously reported in extant work.

III. Test Sample and Descriptive Findings

Sample Firms

We obtained data from the quarterly Compustat industrial and research tapes spanning the interval from the first quarter, 1989 to the fourth quarter, 2005. Sample firms were calendar year-end firms that met two criteria: 1) they had complete time-series data for quarterly CFO reported in accordance with SFAS No. 95, and 2) they had a complete set of quarterly financial statement data needed to operationalize LW's MULT prediction model, namely operating income before depreciation, accounts receivable, inventory, and accounts payable. Table 1 reports the industry representation of our sample of 198 firms.

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

SIC Code	Industry	Number of Firms
28	Chemicals and Allied Products	22
36	Electronic and Other Electrical Equipment	13
73	Business Services	13
35	Machinery, Except Electrical	12
13	Oil & Gas Extraction	8
38	Instruments & Related Products	8
48	Communication	8
20	Food and Kindred Products	7
29	Petroleum and Coal Products	7
45	Transportation by Air	7
33	Primary Metal Industries	6
34	Fabricated Metal Products	6
50	Wholesale Trade – Durable Goods	6
26	Paper and Allied Products	5
37	Transportation Equipment	5
49	Electric, Gas and Sanitary Services	5
And 32 other 2-digit SIC Codes with less than 5 firms		60
	Total Sample	**198**

Table 1 lists the sixteen industries that had five or more firms represented in the sample. A wide spectrum of industries is listed in table 1. For example, the four industries with the greatest two-digit SIC code representation are: Chemicals and Allied products (n=22, 11.1% of sample); Electronic and Other Electrical Equipment (n=13, 6.6% of sample); Business Services (n=13, 6.6% of sample); and Machinery, Except Electrical (n=12, 6.1% of sample). Additionally, there were 32 other two-digit SIC codes that were represented, each of them having fewer than 5 sample firms. This wide spectrum of industry representation underscores the pervasive impact of SFAS No. 95's reporting requirements.

Behavior of Sample Autocorrelation Function

Table 2 provides information on the cross-sectionally derived SACF and partial autocorrelation (PACF) functions of the seasonally-differenced quarterly CFO series.[5] SACF values were computed for each sample firm over 56 quarters beginning with the first quarter, 1989 and ending with the last observation in the identification period, the fourth quarter of 2002. In accordance with the methodology originally popularized by Foster (1977), firm-specific SACF (PACF) values were summed across sample firms and averaged to obtain the values reported in table 2.

Table 2. Cross-Sectional Sample Autocorrelation Function: 1989-2002 (n=198)
(Means and Standard Deviations)

Seasonal Differences (d=0, D=1)

	Lags											
	1	2	3	4	5	6	7	8	9	10	11	12
SACF	.546	.216	-.046	-.284	-.188	-.127	-.079	-.045	-.033	-.010	.009	.011
	(.130)	(.128)	(.187)	(.239)	(.181)	(.158)	(.182)	(.237)	(.173)	(.135)	(.142)	(.178)
PACF	.546	-.157	-.162	-.242	.145	-.104	-.085	-.118	.071	-.041	-.029	-.050
	(.130)	(.144)	(.148)	(.180)	(.155)	(.131)	(.124)	(.134)	(.140)	(.109)	(.106)	(.131)

Note: d = consecutive differencing
D = seasonal differencing
SACF = sample autocorrelation function
PACF = partial autocorrelation function

SACF and PACF values for the seasonally-differenced series reveal time-series behavior of quarterly CFO that is reminiscent of the adjacent (quarter-to-quarter) *and* seasonal (quarter-by-quarter) behavior evidenced by quarterly earnings data. Specifically, we observe exponential decline in SACF values across the first three lags (i.e., .546, .216, and -.046) with a negative spike at the fourth or seasonal lag (i.e., -.284). PACF values exhibit a significant spike at the first lag (i.e., .546) consistent with an autoregressive parameter as well as a gradual decline across seasonal lags consistent with a seasonal moving-average parameter. This time-series behavior is consistent with a more complex cash-flow generating process than the purely seasonal ARIMA processes that have been identified by LSW, among others, analyzing quarterly PCFO series. The exclusion of a host of items routinely reported on the cash-flow statement in accordance with SFAS No. 95 by relatively simplistic algorithms used to generate the quarterly PCFO series (Mulford and Comiskey 2002) has evidently induced substantially different time-series properties on the respective cash-flow series. We discuss and test the predictive performance of a set of quarterly CFO prediction models in the next section.

IV. Cash-Flow Prediction Models

We assess the predictive power of four cash-flow prediction models to examine the predictive ability of CFO. First, LW present predictive evidence documenting enhanced levels of cash-flow predictive ability for a multivariate time-series regression model (MULT). Its structure is provided below:

$$CFO_t = a + b_1 (CFO_{t-1}) + b_2 (CFO_{t-4}) + b_3 (OIBD_{t-1}) + b_4 (OIBD_{t-4}) + b_5 (REC_{t-1}) + \quad (1)$$
$$B_6 (INV_{t-1}) + B_7 (PAY_{t-1}) + e_t$$

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.

Although the MULT model is relatively parsimonious when compared to Wilson's (1987) cross-sectional model which employed 15 independent variables, it still requires considerable time-series data to operationalize. MULT dominated the CFO prediction models tested by LW, however, we are concerned about the generalizability of LW's findings from at least two perspectives. First, LW examined a very small number of firms with sample sizes ranging from 51 to 62 firms depending on the forecast horizon. Second, LW employed quarterly PCFO data constructed using a relatively simplistic algorithm that exhibited time-series properties substantially different from the quarterly CFO series that we examine. We assess the predictive power of MULT in a more rigorous setting using a larger sample of firms (n=198) and employing SFAS #95 quarterly CFO data.

Since virtually no empirical evidence is available on the time-series properties of quarterly CFO, we test two naïve benchmark models that have highly variant time-series properties and have considerable empirical support in the forecasting literature across a wide set of economic time-series. The first of these models is the random walk with drift process (RWD), (010) x (000) with drift in ARIMA notation. This model suppresses seasonal (quarter-by-quarter) correlations, does not require firm-specific parameter estimation aside from the deterministic trend constant, and has proved to be amazingly robust providing relatively accurate predictions for annual earnings (Ball and Watts, 1972) and daily security prices (Fama, 1965), among other variables. It also serves as a control against potential structural changes in the holdout period. It is stipulated below:

$$CFO_t = CFO_{t-1} + a_t + \delta \quad (2)$$

where: CFO_t = operating cash flows at time t

a_t = current disturbance term

δ = deterministic trend constant

The third prediction model is the seasonal random walk with drift process (SRWD), (000) x (010) with drift in ARIMA notation. This model is a parsimonious alternative to the ARIMA models tested by LSW on quarterly PCFO data. It avoids potential measurement error since no autoregressive or moving-average parameters need to be estimated. Foster (1977) provides evidence that the SRWD generates quarterly earnings expectations that result in superior market association metrics (i.e., cumulative average residuals). The SRWD model has also been employed extensively in the earnings-return literature by Bernard and Thomas (1990), among others, as the primary proxy for the security market's expectation of quarterly earnings. Rather than suppressing seasonal effects like the RWD model, its expectations are based exclusively upon seasonal patterns in the CFO series. In this sense, it counterbalances the RWD model which generates expectations exclusively on adjacent (i.e., quarter-to-quarter) effects. The SRWD model is provided below:

$$CFO_t = CFO_{t-4} + a_t + \delta \qquad (3)$$

where: CFO_t = operating cash flows at time t

a_t = current disturbance term

δ = deterministic trend constant

The fourth prediction model is the BR ARIMA process attributed to Brown and Rozeff (1979) as a candidate model for quarterly earnings, (100) x (011) in ARIMA notation. It is especially relevant to our analysis since it captures the adjacent (quarter-to-quarter) and seasonal (quarter-by-quarter) behavior in the seasonally-differenced quarterly CFO series that we document in Section III. While it is more complex than the RWD and SRWD models due to the joint estimation of regular autoregressive and seasonal moving-average parameters, it is considerably more parsimonious than the MULT model. The BR model is univariate in nature, simply relying upon lagged values of the quarterly CFO series in sharp contrast to the host of independent variables included in MULT. It may be characterized as follows:

$$CFO_t = CFO_{t-4} + \varphi_1 (CFO_{t-1} - CFO_{t-5}) + a_t - \Theta_1 (a_{t-4}) \qquad (4)$$

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 Results

One-step-ahead predictions of CFO were generated in an *ex ante* fashion by the four cash-flow prediction models. Models were estimated initially using data beginning with the first quarter of 1989 and ending with the fourth quarter of 2002 in order to generate CFO predictions for the first quarter of 2003. Models were subsequently re-estimated by adding the actual first quarter CFO for 2003 to the existing data base prior to generating the second quarter CFO predictions in 2003. This process was repeated sequentially and the models were re-estimated until all twelve one-step-ahead CFO predictions over the three year holdout period (2003-2005) were obtained. We computed two error metrics, mean absolute percentage error (MAPE) and mean squared error but only report MAPE values since the overall tenor of the results was unaffected by the choice of error metric.[6]

Table 3 contains the MAPE metrics for the cash-flow prediction models (RWD, SRWD, MULT, BR) for each individual quarter (1st, 2nd, 3rd, 4th), year (2003, 2004, 2005), and on a pooled basis across all quarters and years. We assessed whether the accuracy of the prediction models was significantly different by using the Friedman ANOVA ranks test (Hollander and Wolfe 1999). Specifically, the prediction model yielding the smallest absolute percentage error for each firm was given a rank of one, the next smallest error was given a rank of two and so on until the model yielding the largest error was given a rank of four. We also provide the average rank of each prediction model by quarter and on a pooled basis, Friedman's S-statistic and its associated significance level.

Table 3. Mean Absolute Percentage Errors of One-Step-Ahead CFO Predictions (2003-2005)

	1st Qtr		2nd Qtr		3rd Qtr		4th Qtr		Year			Pooled	
	Avg Rank	MAPE	Avg Rank	MAPE	Avg Rank	MAPE	Avg Rank	MAPE	2003	2004	2005	Avg Rank	MAPE
Model	n=198		n=198		n=198		n=198		n=792	n=792	n=792	n=2,376	
RWD	3.19	.947	3.06	.614	3.05	.486	2.97	.394	.613	.614	.604	3.07	.610
SRWD	1.94	.573	2.47	.492	2.64	.454	2.76	.400	.505	.461	.474	2.45	.480
MULT	2.48	.737	2.51	.519	2.34	.402	2.35	.330	.506	.482	.502	2.42	.497
BR	2.39	.698	1.95	.407	1.98	.347	1.93	.281	.456	.423	.420	2.06	.433
Friedman ANOVA S-Statistic	283.56		220.18		220.07		225.60					740.66	
Significance Level	.001		.001		.001		.001					.001	

where:

RWD = random walk with drift model
SRWD = seasonal random walk with drift model
MULT = Multivariate time-series regression model
BR = Brown-Rozeff (100) x (011) ARIMA model

The primary finding reported in Table 3 is that there is a statistically significant difference (p=.001) in the average ranks of the MAPEs of the CFO prediction models for all individual quarters and on a pooled basis across quarters and years. For example, the best-performing CFO prediction model on a *pooled* basis was BR (.433) outperforming SRWD (.480), MULT (.497), and RWD (.610).[7] The superior performance of the BR model is consistent, pertaining to all years in the holdout period (2003, 2004, and 2005) as well as for quarters two, three and four. These findings are in marked contrast to those reported by LW where the superiority of the MULT model was reported. Perhaps LW's use of a simplistic algorithm to approximate the CFO series coupled with their relatively small test samples ranging from 51 to 62 firms may be partially responsible for the lack of generalizability of their findings. Finally, the SRWD model is the best performing model (.573) in the first quarter outperforming the BR (.698), MULT (.737), and RWD (.947) models.

Table 4 provides all possible pairwise-comparisons of the prediction models based on the significant Friedman ANOVA on the *pooled* predictive results reported in Table 3. In all comparisons, the BR model exhibits significantly (p = .001) smaller ranks than the RWD, SRWD, and MULT models. Untabulated comparisons for quarters two, three, and four reveal similar dominance of the BR model. The only exception pertains to the first quarter predictions where the SRWD model exhibits significantly (p = .001) smaller ranks than all other models.

Inspection of MAPE levels in the first quarter in Table 3 reveals values that are considerably larger than those reported in other quarters. A potential explanation for these inflated first-quarter errors pertains to the fact that the fourth quarter of the preceding year is the conditioning quarter upon which first-quarter extrapolations for the RWD, MULT, and BR models are based. It is possible that fourth quarter CFOs might contain incremental measurement error to the extent that fourth quarter CFOs are affected by the settling-up effect wherein estimated quarterly results are reconciled with more accurate annual figures.[8] The indirect method of computing CFO data highlights the similarities in the CFO and earnings series. Therefore, prediction models like the RWD, MULT, and BR models that are influenced by adjacent (quarter-to-quarter) effects might be negatively impacted by the presence of incremental measurement error in the most recent quarter. In contrast, the SRWD model provides the most accurate predictions for the first quarter. The SRWD model, unlike the other CFO prediction models that we examine, is not influenced by adjacent (quarter-to-quarter) effects. It is a purely seasonal prediction model.

Table 4. Paired Comparisons Based on Ranks of Prediction Models: Pooled MAPEs

Model (Avg. Rank)	**SRWD (2.45)**	**MULT (2.42)**	**BR (2.06)**
RWD (3.07)	SRWD***	MULT***	BR***
SRWD (2.45)		___	BR***
MULT (2.42)			BR***

where:

RWD = random walk with drift model
SRWD = seasonal random walk with drift model
MULT = Multivariate time-series regression model
BR = Brown-Rozeff (100) x (011) ARIMA model
*** = significant at p=.001
___ = insignificant

VI. Additional Analysis

Firm Size

Baginski et al. (1999) argue that firm size is an economic determinant of earnings persistence based on the notion that large firms are better diversified and exhibit more stable growth patterns than small firms. We provide evidence on whether the predictive dominance of the BR model pertains to firms of varying size or is constrained to particular size strata(s). We also provide new predictive evidence on whether firm size systematically affects the accuracy of CFO predictions. To do so we partitioned the 198 firm sample equally into small, medium, and large firm subsets (n=66) based on the book value of total assets reported on December 31, 2002, the end of the model identification period.

Panel A of table 5 reports MAPE values of pooled one-step ahead predictions across the 2003-2005 forecast horizon for the RWD, SRWD, MULT, and BR ARIMA models. We employed the Friedman ANOVA ranks test separately for each size strata and determined that the MAPEs of the CFO prediction models were significantly different (p = .001). Untabulated matched-paired comparisons indicate that the BR model provides significantly smaller MAPEs (p=.001) than the RWD, SRWD, and MULT models for each size partition. Therefore, the predictive dominance of the BR model is pervasive and applies to firms of varying size.

We observe a monotonic decline in MAPE values when moving from small to large firms across all four prediction models. To determine whether this observed decline in MAPEs is significant, we conducted a K-sample median test separately on the pooled MAPEs for each model across the three size partitions. Panel B of table 5 indicates that the chi-square statistics are significant (p = .001) for the SRWD, MULT, and BR ARIMA models and insignificant (p=.630) for the least accurate prediction model, RWD.

We employed a Mann-Whitney U-test to determine which strata comparisons contributed to the overall significance levels pertaining to the SRWD, MULT, and BR models. Panel C of table 5 reveals that the MAPE values of *both* medium and large firms were significantly (p = .001) smaller than those of small firms for all models. Comparisons between the MAPEs of medium and large firms evidenced more contextual findings. The MAPE values for the SRWD and MULT models for medium and large firms were significantly different (p = .037 and p = .096, respectively) while similar comparisons for the BR model were insignificant (p = .186). Overall, the size-partitioned MAPE comparisons support the generalization that CFO predictions of larger firms are more accurate than those of smaller firms.

Table 5. Model Forecast Errors Partitioned by Size

Panel A: Pooled MAPEs across 2003-2005: Partitioned by Size

	Small Firms (n=792)		Medium Firms (n=792)		Large Firms (n=792)	
Model	**Avg. Rank**	**MAPE**	**Avg. Rank**	**MAPE**	**Avg. Rank**	**MAPE**
RWD	2.84	.611	3.13	.610	3.24	.609
SRWD	2.47	.556	2.47	.460	2.41	.423
MULT	2.51	.570	2.41	.473	2.34	.448
BR	2.19	.510	1.99	.403	2.01	.386
Friedman ANOVA S-Statistic	10,463.6		10,817.5		10,940.1	
Significance Level	.001		.001		.001	

Panel B: K-Sample Median Test on Size Partitions

	MODEL			
	RWD	**SRWD**	**MULT**	**BR**
Chi-square (2 degrees of Freedom)	0.92	33.11	46.48	43.17
p-value	0.63	.001	.001	.001

Panel C: Mann-Whitney U-Tests on MAPE values: Pairwise size comparisons

Model	**Strata Comparison**	**p-value**
SRWD	small versus medium	.001
	small versus large	.001
	medium versus large	.037
MULT	small versus medium	.001
	small versus large	.001
	medium versus large	.096
BR	small versus medium	.001
	small versus large	.001
	medium versus large	.186

where:
RWD = random walk with drift model
SRWD = seasonal random walk with drift model
MULT = Multivariate time-series regression model
BR = Brown-Rozeff (100) x (011) ARIMA model

Expanded Sample

Despite the fact that our primary sample of firms (n=198) surpassed the small-sample sizes of Hopwood and McKeown (1992) and LW, we were still concerned about the generalizability of our findings. While the RWD, SRWD, and BR ARIMA models have relatively modest data input requirements (i.e., simply a time series of quarterly CFO data), the MULT model required quarterly time series of several financial statement subcomponents (i.e., operating income before depreciation, accounts receivable, inventory, and accounts payable) in addition to the quarterly CFO requirement. Since MULT's CFO predictions were systematically dominated by the BR model, we conducted a supplementary analysis that eliminated the data requirements of MULT and deleted it from the set of CFO prediction models. This increased sample size dramatically to 745 firms.

Panel A of table 6 contains the MAPE metrics of the three cash-flow prediction models (i.e., RWD, SRWD, and BR) for each individual quarter (1st, 2nd, 3rd, 4th), year (2003, 2004, 2005) and on a pooled basis across all quarters and years. With the exception of the first-quarter MAPEs, the BR model provides the most accurate MAPEs across quarters, years, and on a pooled basis. The Friedman ANOVA ranks test indicates that the ranks of the pooled MAPEs are significantly different (p=.001). Panel B of table 6 shows that in all comparisons the BR model exhibits significantly (p=.001) smaller ranks than the RWD and SRW models. These results enhance the generalizability of our findings in support of the BR model as a quarterly CFO prediction model.

Table 6. MAPEs of Expanded Sample (n=745)

Panel A: Friedman ANOVA analysis: Pooled MAPEs

Model	**Quarter**			**MAPEs**	**Year**				**Pooled**
	1	**2**	**3**	**4**	**2003**	**2004**	**2005**	**Avg. Rank**	
RWD	.939	.614	.484	.423	.620	.607	.618	2.32	.615
SRWD	.607	.547	.497	.452	.551	.512	.513	1.98	.526
BR	.716	.461	.387	.331	.490	.465	.467	1.70	.474

Friedman ANOVA S-Statistic	1720.26
Significance Level	.001

Panel B: Paired Comparisons Based on Ranks of Prediction Models: Pooled MAPEs

Model	**SRWD**	**BR**
(Avg. Rank)	**(1.98)**	**(1.70)**
RWD **(2.32)**	SRWD***	BR***
SRWD **(1.98)**		BR***

where:

RWD = random walk with drift model
SRWD = seasonal random walk with drift model
BR = Brown-Rozeff (100) x (011) ARIMA model
******* = significant at p=.001

VII. Concluding Remarks

Our findings contribute to the growing literature on quarterly cash-flow prediction models. The methodology that we employ has a distinctive feature relative to extant work, the employment of quarterly CFO data reported in accordance with SFAS No. 95. Previous empirical work such as Hopwood and McKeown (1992) and LSW, among others, analyzed a proxy series (i.e., PCFO) constructed via a relatively simplistic algorithm. We provide descriptive evidence based on SACF analysis that the time-series properties of quarterly CFO are at variance with the exclusively seasonal characterization of quarterly PCFO identified by LW. Quarterly CFO exhibit both adjacent (quarter-to-quarter) *and* seasonal (quarter-by-quarter) relationships reminiscent of the time-series properties of quarterly earnings. Mulford and Comiskey (2002) discuss numerous items that are included in the cash-flow statement in accordance with SFAS No. 95, but are not considered by relatively simplistic algorithms used to construct the quarterly PCFO series. Evidently, the inclusion of such items may be responsible for our descriptive finding that the time-series properties of quarterly CFO differ systematically from the time-series properties of quarterly PCFO.

We identify the (100) x (011) BR ARIMA model as a candidate expectation model for reported quarterly CFO. It has both autoregressive and seasonal moving-average parameters to capture the adjacent and seasonal autocorrelation patterns that we document in the quarterly CFO series. Consistent with its descriptive validity, the BR model significantly outpredicts the MULT model popularized by LW as well as two benchmark models, RWD and SRWD. Supplementary analyses provide evidence that: (1) the forecast errors of larger firms are significantly smaller than the forecast errors of smaller firms, and (2) the predictive ability of the BR model is robust when we test it upon an expanded sample of firms (n=745) obtained by eliminating the considerable data requirements of MULT. These findings should be of considerable interest to decision makers, policy makers and researchers in accounting who employ quarterly cash-flow prediction models.

References

Baginski, S. P., K. S. Lorek, G. L. Willinger, and B. C. Branson. 1999. The relationship between economic characteristics and alternative annual earnings persistence measures. *The Accounting Review* 74: 105-20.

Ball, R. J. and R. L. Watts. 1972. Some time series properties of accounting income. *Journal of Finance* 27: 663-81.

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

Bernard, V. L. and J. Thomas. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13: 305-40.

Bowen, R., D. Burgstahler, and L. Daley. 1986. Evidence on the relationships between earnings and various measures of cash flow. *The Accounting Review* 61 (October): 713-25.

Brown, L. D. and M. S. Rozeff. 1979. Univariate time-series models of quarterly accounting earnings per share: A proposed model. *Journal of Accounting Research* 17 (Spring): 179-89.

Dechow, P. M., S. P. Kothari, and R. L. Watts. 1998. The relation between earnings and cash flows. *Journal of Accounting and Economics* 25: 133-68.

Fama. E. 1965. Random walks in stock market prices. *Financial Analysts Journal* September-October 1965: 55-59.

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

Financial Accounting Standards Board. 1987. *Statement of Financial Accounting Standards No. 95: Statement of Cash Flows.* Stamford, CT: FASB.

Foster, G. 1977. Quarterly accounting data: Time-series properties and predictive ability results. *The Accounting Review* 52 (January): 1-21.

Hollander, M., and D. Wolfe. 1999. *Nonparametric Statistical methods. 2nd ed.* New York, NY, John Wiley and Sons, Inc.

Hopwood, W. S., and J. C. McKeown. 1992. Empirical evidence on the time-series properties of operating cash flows. *Managerial Finance* 18: 62-78.

Kim, M. and W. Kross. 2005. The ability of earnings to predict future operating Cash flows has been increasing – not decreasing. *Journal of Accounting Research* 43: 753-80.

Lorek, K. S., T. F. Schaefer, and G. L. Willinger. 1993. Time-series properties and predictive ability of funds flow variables. *The Accounting Review* 68 (January): 151-63.

Lorek, K. S. and G. L. Willinger. 1996. A multivariate time-series prediction model for cash-flow data. *The Accounting Review* 71 (January): 81-101.

Mulford, C. W. and E. E. Comiskey. 2002. *The Financial Numbers Game:* John Wiley & Sons, Inc. New York, NY.

Wilson, G. P. 1987. The incremental information content of the accrual and funds components of earnings after controlling for earnings. *The Accounting Review* 62 (April): 293-322.

Endnotes

[1] We employ customary (pdq) X (PDQ) ARIMA notation where (p,P) are regular autoregressive and seasonal autoregressive parameters; (d,D) are consecutive and seasonal differencing; and (q,Q) are regular moving-average and seasonal moving-average parameters.

[2] The BR ARIMA model also significantly outperforms the (000) x (100) seasonal autoregressive model and the (000) x (011) seasonal moving-average model identified by LSW.

[3] Bowen et al. (1986) provide a particularly lucid discussion of the importance of cash-flow prediction in the above settings.

[4] Brown (1993) discusses how disaggregating annual earnings into quarterly earnings results in the identification of quarterly ARIMA models that have significantly greater predictive power than simpler annual models.

[5] Examination of the SACFs and PACFs of the raw data, consecutively-differenced, and consecutively and seasonally differenced CFO series did not yield incremental insights and are available from the authors.

[6] Similar to LW, all forecast errors greater than 100 percent were truncated to 100 percent to minimize the effect of explosive errors or outliers. Across the pooled predictions reported in table 3, the BR ARIMA model's predictions were truncated less frequently (21.8%) than those of the SRWD (22.1%), MULT (25.6%), and RWD (32.4%) models.

[7] We also tested the (000) x (100) SAR and (000) x (011) SMA ARIMA models popularized by LSW. The SAR model exhibited a pooled MAPE of .486 while the SMA model had a pooled MAPE of .467. Both models were significantly (p=.001) outperformed by the BR ARIMA model in untabulated predictive comparisons.

[8] See Bathke and Lorek (1984) for a discussion of the settling-up effect with respect to quarterly earnings.