Long-Term Earnings Forecast Models for Nonseasonal Firms

*Allen W. Bathke, Jr., **Kenneth S. Lorek, and ***G. Lee Willinger
Florida State University, Northern Arizona University, and The University of Oklahoma

This paper examines the long-term predictive ability of earnings forecast models for a sample of 167 firms whose quarterly earnings numbers exhibit nonseasonal behavior. Empirical evidence is provided showing that: 1) a large number of firms (n=167, i.e., 28.2% of the sample) exhibit nonseasonal patterns in their quarterly earnings series; 2) the use of quarterly ARIMA forecast models does not result in enhanced annual earnings predictions versus annual ARIMA models for nonseasonal firms; 3) the size effect documented by Bathke et al. (1989) for short-term quarterly earnings forecasts also pertains to long-term, annual earnings forecasts: and 4) larger firms' earnings series display enhanced levels of earnings persistence versus those of smaller firms.

Key Words: Nonseasonal firms, Earnings forecasting, Box-Jenkins time-series analysis

Introduction

Investors in securities markets search for information germane to making investment decisions. Earnings is clearly a primary variable of interest to the investment community. Investors view earnings with great interest since it represents a summary measure of performance and is believed to convey information about a firm's future cash-flow prospects (FASB, 1994 and Elliott, 2006). Lorek and Willinger (1996) and Kim and Kross (2005) provide empirical evidence that accrual accounting information is useful in predicting future cash flows. The importance that investors place on earnings and forecasts of earnings has led to a considerable amount of research in the earnings forecasting arena. Within this area, one line of research has focused on the identification and development of statistically-based earnings forecast models.

This stream of research has concentrated on forecasting models that are appropriate for predicting the quarterly earnings numbers of firms (Brown, 1993). Although such works do not assume that the degree of seasonality is constant across firms, their exclusive use of seasonal ARIMA model structures implies that all firms exhibit seasonal patterns in their quarterly earnings series.[1] Researchers have attempted to identify a common-structure, seasonal ARIMA model for all firms, while allowing for firm-specific parameter estimation.[2] For example, the Foster (1977) model assumes that seasonal earnings changes follow an autoregressive process where the autoregressive parameter is estimated individually for each firm. The model attributed to Brown and Rozeff (1979) assumes a similar process with the addition of a seasonal moving-average parameter.

While previous work has shown that a majority of firms exhibit seasonal tendencies (Lorek and Bathke, 1984), research also indicates that a sizable number of firms exhibit quarterly earnings patterns that are clearly nonseasonal. Although the percentage of nonseasonal firms identified in earlier work has been relatively small, the merger and acquisition activity of the 1980s, which resulted in diversification of businesses into alternative product lines and services, makes it plausible that increasing numbers of firms have quarterly earnings series that are nonseasonal.[3] While managers may adopt new product lines and perform services that are highly seasonal, they may choose to diversify into new areas that provide counterbalancing seasonal effects. For example, a toy manufacturer may seek to add product lines with seasonal effects in the spring to offset partially the concentration of toy sales in the winter months.

A sub-sample of 167 nonseasonal firms (i.e., 28.2%) is detected from a sample of 593 firms in the current study, far greater than the 29 nonseasonal firms (i.e., 12.1% of the sample) examined by Lorek and Bathke (1984). A set of both quarterly and annual, nonseasonal ARIMA earnings forecast models for these 167 firms is identified to determine whether quarterly models are better than annual models for firms that only exhibit nonseasonal earnings behavior. Brown (1993) cites evidence that the use of quarterly ARIMA models yields annual earnings forecasts that are 15-21% more accurate than simply employing an annual model. Such increases in accuracy pertain only to one year-ahead annual earnings predictions, not the longer forecast horizons examined in the current study. Since the main benefit of quarterly modeling pertains to the identification of seasonal effects that are captured by using seasonal differencing and/or seasonal parameters, it is not surprising that seasonal firms would benefit from modeling of their quarterly earnings series. The nonseasonal firms in our sample, however, do not exhibit such seasonal characteristics. The benefits of quarterly modeling versus annual modeling are less clear for nonseasonal firms.

Brown and Han (2000) show that 17% of firms possess quarterly earnings-generating processes that are nonseasonal and can be described by an AR1 model. They also find that stock market prices do not fully reflect the implications of current quarterly earnings for future quarterly earnings for nonseasonal firms. These results underscore the importance of analyzing quarterly-earnings expectation models for firms that exhibit idiosyncratic, nonseasonal time-series patterns.

The work of Ohlson (1995) and Feltham and Ohlson (1995) underscores the importance of predictions of long-term earnings to the valuation process. These works illustrate that market value can be expressed as a function of book value plus the present value of future expected abnormal earnings [Ohlson, 1995, p. 664]. Since expected abnormal earnings represents forecasted earnings reduced by a charge for capital, it is clear that long-term predictions of earnings play a central role in explaining firm value under the Feltham and Ohlson (1995) model. As discussed by Bernard (1995, pp. 734-35), the work of Feltham and Ohlson reduces the importance of explaining stock price changes and emphasizes the forecasting of long-term earnings. The aforementioned studies also underscore the importance of generating long-term, annual earnings predictions as opposed to one-year ahead predictions.[4] Therefore, empirical evidence is provided in the current study on the accuracy of 1-5 year-ahead annual earnings forecasts across two time periods: 1992-1996 and 1997-2001.

Research has also indicated that the short-term predictive ability of earnings numbers (i.e., one-quarter ahead) is sensitive to firm size (Bathke, Lorek and Willinger, 1989, among others). The current study provides an assessment of whether firm size has a similar impact on the long-term predictive ability of annual earnings. After our sample of nonseasonal firms is partitioned into small, medium and large firm subsets, the accuracy of long-term, annual earnings predictions is found to be positively related to firm size. That is, long-term, annual earnings predictions are more accurate for large firms than for small firms. Large firms are found to also have more persistent earnings streams than small and medium-sized firms. It appears that the more persistent earnings streams of large firms enable the annual ARIMA models to be estimated with greater precision than similar models for small and medium-sized firms.

Financial analysts' forecasts of earnings are, in general, more accurate than the statistically-based models that are examined in this paper. However, Williams (1995), among others, has stated that statistically-based models have long been used by financial analysts and econometricians to forecast earnings and conduct firm valuations.[5] Ali, Klein and Rosenfeld (1992) report that analysts' earnings forecasts are biased and their forecast errors are serially correlated. They conclude that "analysts do not properly recognize the time-series properties of earnings when setting expectations of future earnings." (p. 184) These factors underscore the importance of investigating firms that exhibit idiosyncratic quarterly earnings time-series patterns such as the nonseasonal firms in the current study's sample. This analysis of statistically-based models may increase the accuracy of the input data that analysts combine with firm-specific, industry, and macroeconomic data to formulate their earnings forecasts.[6]

Time-series earnings forecasts are less costly alternatives to those of analysts and may be the only feasible source of earnings expectations for firms that are relatively small and uncovered by analysts. Statistically-based forecasts may be an important component in the ill-specified, complex, multivariate process that analysts employ to generate their earnings expectations. In this setting, Imhoff and Pare (1982) and Brown, Richardson and Schwager (1987) provide empirical evidence that the dominance of analysts' earnings forecasts versus statistically-based models is inversely related to the length of the forecast horizon. This provides added incentive to assess the long-term predictive ability of statistically-based, earnings expectation models over the 1-5 year forecast horizon that are employed in the current study.

Research Design

DATA SAMPLING PROCEDURES

Initially, a sample of 593 calendar, year-end firms which had complete time-series data on quarterly net income before extraordinary items for each quarter during the 1978 to 1996 time period on the Quarterly Compustat tapes was obtained. To partition this sample of firms with respect to the seasonality (or lack thereof) of the quarterly earnings stream, sample autocorrelation functions (SACFs) of the *quarterly* earnings series for each firm using a 56-observation data base (1978-1991) were computed. A filter for nonseasonality that was identical to the one employed originally by Lorek and Bathke (1984) was used. This resulted in classifying 167 of 593 sample firms as nonseasonal. Specifically, any firm was labeled nonseasonal if all three lag multiples of the seasonal span of the SACF (i.e., 4, 8 and 12) were less than the respective value of the standard deviation associated with that lag. To avoid potential nonstationarity problems, this test was conducted on the consecutively-differenced series. Panel A of Table 1 displays the cross-sectional SACF of the undifferenced, quarterly earnings series (i.e., d=0, D=0) for the 167 nonseasonal firm sample. It reveals the lack of spikes at lags 4, 8 and 12 (i.e., .224, .091 and .021, respectively) of the SACF. Panel A also depicts the SACF of the consecutively-differenced, quarterly earnings series (i.e., d=1, D=0). It also reveals no seasonal spikes at lags 4, 8 and 12 (i.e., -.024, .010, and .013) which underscores the nonseasonal quarterly earnings characteristics of the firms in our 167 nonseasonal firm sample. Panel B presents the SACF function of the *annual* earnings series computed over the same identification period. Since we are limited to the 14 years between 1978-1991, the number of lags in the *annual* SACF has been reduced to six.

Table 1
Cross-Sectional Sample Autocorrelation Function for the 167 Nonseasonal Frims: 1978-1991 (Means and Standard Deviations)

Panel A: Quarterly Earnings

d D	1	2	3	4	5	6	7	8	9	10	11	12
0 0												
mean	.354	.296	.254	.224	.165	.131	.108	.091	.062	.043	.034	.021
std. Dev.	(.133)	(.157)	(.171)	(.181)	(.187)	(.193)	(.197)	(.200)	(.202)	(.205)	(.207)	(.209)
1 0												
mean	-.388	-.013	-.008	-.024	-.011	-.018	-.002	.010	-.013	-.010	-.001	.013
std. Dev.	(.135)	(.157)	(.160)	(.162)	(.162)	(.163)	(.165)	(.166)	(.167)	(.168)	(.169)	(.171)

Panel B: Annual Earnings

d D	1	2	3	4	5	6
0 0						
mean	.322	.114	.011	-.060	-.102	-.145
std. Dev.	(.267)	(.309)	(.325)	(.335)	(.342)	(.349)
1 0						
mean	-.220	-.075	-.041	-.036	-.219	-.222
std. Dev.	(.277)	(.307)	(.319)	(.327)	(.335)	(.340)

where: d = consecutive differencing and D=seasonal differencing

Sample Profiles and Size Partitions

Table 2 presents profile information on the 593 firm sample partitioned on two dimensions: 1) seasonal behavior [i.e., nonseasonal firms (n=167) and seasonal firms (n=426)] and 2) size (i.e., small, medium and large). Bathke et al. (1989) present empirical evidence that the accuracy of statistically-based, short-term earnings predictions (i.e., one-quarter ahead) is directly related to firm size. Specifically, short-term forecast errors are systematically smaller (i.e., earnings forecasts are more accurate) for large firms than for small firms. The sample was partitioned into size strata based on the market value of common stock equity determined on December 31, 1991, the end of the model identification period, to examine whether firm size has a systematic effect on long-term, annual earnings predictions.

Table 2
Profile Information on Sample Firms*

Panel A: Nonseasonal Firms (n=167)

	ANNUAL EARNINGS *F/Y/E 12/31/91*		Market Value of COMMON STOCK EQUITY *at 12/31/91*		ANNUAL SALES *F/Y/E 12/31/91*	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Total (n=167)	$138.12	$30.42	$3,752.08	$1,323.45	$4,754.35	$1,943.08
Small (n=56)	-7.67	2.20	167.86	104.47	465.17	235.45
Medium (n=56)	30.28	56.50	1,493.49	1,327.72	2,569.04	1,926.47
Large (n=55)	396.38	287.86	9,701.11	6,843.79	11,346.54	6,776.90
Panel B: Seasonal Firms (n=426)						
Total (n=426)	$162.99	$48.33	$3,657.95	$937.55	$4,145.24	$1,138.21
Small (n=142)	-1.53	4.28	150.08	111.21	412.68	199.62
Medium (n=142)	51.51	59.34	1,076.05	937.55	1,695.61	1,041.34
Large (n=142)	438.98	262.82	9,747.72	4,583.50	10,327.44	4,303.30

*all numbers in $ millions
F/Y/E = fiscal year-end

Across the entire sample, nonseasonal firms are, on average, larger than seasonal firms [e.g., median market values (in millions) of common stock equity at December 31, 1991 of $1,323.45 vs $937.55], generate greater levels of sales revenue [e.g., median 1991 sales (in millions) of $1,943.08 vs. $1,138.21], but are less profitable than seasonal firms [e.g. median 1991 net earnings (in millions) of $30.42 vs $48.33]. Table 2 also provides corresponding values on these same variables for small, medium, and large firm subsets for both the nonseasonal and seasonal samples.

Forecast Models

A considerable amount of research in the earnings forecast arena has been directed at assessing the time-series properties of quarterly earnings data (Brown, 1993). Such studies have focused on the development of seasonal quarterly earnings ARIMA forecast models for all firms. Much of this work has been directed at identifying a common-structure, ARIMA forecast model. Researchers have examined the cross-sectional SACFs of various forms of the quarterly earnings series (e.g., levels, consecutive differences, seasonal differences and combinational differences) across sample firms. Three candidate models have emerged from this process. Using customary (pdq) X (PDQ) notation, they are the Foster (1977) (100) X (010) with drift model; the Brown Rozeff (1979) (100) X (011) model and the Griffin (1977) -Watts (1975) (011) X (011) ARIMA models where p,P represents the number of regular and seasonal autoregressive parameters, d,D represents the level of consecutive and seasonal differencing, and q,Q represents the number of regular and seasonal moving-average parameters. Brown (1993) points out that these three seasonal ARIMA models form the core of the quarterly earnings time-series literature. Such seasonal models are misspecified for the nonseasonal firms in our sample. As Lorek and Bathke (1984) state "….the use of seasonal differencing and/or seasonal parameters resulted in (1) overdifferencing of the data, (2) parameter redundancy, (3) violation of the principle of parsimony, and (4) reduced levels of predictive ability" (p. 378) on the nonseasonal firms that they examine.

Based upon analysis of the cross-sectionally derived, quarterly SACF in Panel A of Table 1, three common-structure, nonseasonal, quarterly forecasts models were identified. These include:

1) **The (100) X (000) ARIMA model [Hereafter, QAR1]:** This is a simple autoregressive process of order one identified on the level series. The QAR1 model was identified due to the monotonic decline in the SACF values across the first four lags of the level series in panel A of Table 1 (i.e., .354, .296, .254 and .224) Additionally, Lorek and Bathke (1984) provide predictive evidence supportive of this model.
2) **The (010) X (000) Quarterly Random Walk with drift model [Hereafter, QRWD]:** This model is a parsimonious alternative to the QAR1 model where the autoregressive parameter is set equal to one. In this model, the most recent quarterly earnings figure (adjusted for the drift term) provides the expectation for the n-step ahead earnings forecasts.
3) **The (011) X (000) ARIMA model: [Hereafter, QDMA1]:** This is a simple moving-average process on the consecutively-differenced series. The QDMA1 model was identified due to the spike of -.388 at the first lag of the consecutively-differenced SACF.

The next set of forecast models is comprised of annual models that were identified by using the annual SACF values in Panel B of Table 1. Close inspection of the annual SACFs provided support for the identical model structures that were identified on the quarterly earnings series. These include:

1) **The (100) ARIMA model [Hereafter, AAR1]:** This model is identical in structure to the QAR1 model. Support is provided by the monotonic decline in the annual SACF values across the first three lags of the level series in Panel B of Table 1 (i.e., .322, .114, and .011). This model is distinguished from the QAR1 model since it is estimated using annual earnings data rather than quarterly earnings data.
2) **The (010) Annual Random Walk with drift model [Hereafter, ARWD]:** This model is a parsimonious alternative to AAR1 where the autoregressive parameter is set equal to one. It is distinguished from the QRWD model since it is estimated using annual earnings data. Ball and Watts (1972), among others, provide support for the ARWD structure.
3) **The (011) ARIMA model [Hereafter, ADMA1]:** This model is identical in structure to the QDMA1 model. Support is provided by examining the consecutively-differenced, annual SACFs where the first lag exhibits a spike of -.220. It is distinguished from the QDMA1 model since it is estimated using annual earnings data.

Examination of both the quarterly and annual SACFs did not result in the identification of any additional model structures.

Predictive Findings

The predictive ability of the quarterly and annual models across the 1992-1996 holdout period was assessed. Specifically, one-through-twenty-step-ahead quarterly earnings forecasts were generated for each quarterly model beginning with the first quarter of 1992 and ending with the fourth quarter of 1996. The four quarterly forecasts (i.e., quarters 1 through 4) were summed within a given year to form the annual earnings forecast for that year. Thus, the 1 through 4 step-ahead quarterly earnings forecasts were summed to obtain the annual earnings forecast for 1992. The 5 through 8 step-ahead quarterly earnings forecasts were summed to obtain the annual earnings forecast for 1993, etc. For the annual models, one-through-five-step-ahead annual earnings forecasts were generated beginning with 1992 and ending with 1996. Thus, the forecast for 1992 was a 1 year-ahead forecast while the forecast for 1993 was a 2 year-ahead forecast, etc. Similar to Bathke et al. (1989), absolute percentage errors (APEs) were calculated and all forecast errors greater than 100 percent were truncated to 100 percent prior to statistical testing. Table 3 displays the mean APEs (MAPEs) for the forecast models for each forecast horizon (i.e., 1-5 years-ahead) as well as on an aggregate basis across forecast horizons.

Table 3
Mean Absolute Percentage Errors of Nonseasonal Firms

	1 Year Ahead	2 Year Ahead	3 Year Ahead	4 Year Ahead	5 Year Ahead	Pooled
QRWD	.575	.629	.609	.681	.647	.628
QDMA1	.556	.612	.617	.659	.643	.617
QAR1	.549	.597	.572	.636	.634	.598
ARWD	.580	.624	.615	.662	.661	.628
ADMA1	.554	.604	.613	.646	.665	.617
AAR1	.518	.571	.564	.616	.620	.577
Friedman S-Statistic						4.18
P-value						.52

Where:

QRWD = Quarterly random walk with drift model
QDMA1 = Quarterly differenced, first-order moving-average model
QAR1 = Quarterly first-order autoregressive model
ARWD = Annual random walk with drift model
ADMA1 = Annual differenced, first-order moving-average model
AAR1 = Annual first-order autoregressive model

Table 3 reveals that the AAR1 Model is the most accurate prediction model overall with a pooled MAPE of .577. These results also pertain to each forecast horizon since the AAR1 model provides the smallest MAPEs for every forecast horizon in the holdout period (i.e., 1-5 years-ahead). The next best model is the QAR1 Model with a pooled MAPE of .598. Although the AAR1 Model consistently demonstrated the smallest MAPEs, non-parametric statistical tests yield Friedman S-Statistics that were insignificant at conventional levels across forecast horizons. Nevertheless, these results are noteworthy given the evidence presented in Brown (1993), among others, that the use of quarterly versus annual ARIMA models improves forecast accuracy by 15-21%. No such improvement in predictive ability is evidenced in the current study.

Table 4 presents MAPE information pertaining to the accuracy of the forecast models on the nonseasonal sample that was partitioned into small (n=56), medium (n=56) and large (n=55) firm strata. These results related to partitioning extend Bathke et al.'s (1989) findings on the size effect for short-term earnings predictions (i.e., one-quarter ahead) to the long-term prediction of earnings (i.e., one-to-five years ahead). We observe in Table 4 that the pooled MAPEs of the best forecast model for large firms (i.e., ADMA1 = .497) are substantially smaller than the best model for small firms (i.e., AAR1 = .686). The dominance of the annual, nonseasonal models is most pronounced for the large firm strata. The pooled MAPEs for the ADMA1 Model are .032 lower than the best quarterly, seasonal model, QDMA1 (i.e., .497 vs. .529) and the difference across models is statistically significant for large firms (p=.001). Inspection of the medium (n=56) strata of firms reveals virtually identical performance for the best quarterly, seasonal (i.e., QAR1 = .536) and the best annual, nonseasonal models (i.e., AAR1 = .541). The difference between models was substantially less than that displayed by the larger firms and it was insignificant (p=.26). Finally, the best annual, nonseasonal model (i.e., AAR1 = .686) for the small (n=56) firm strata outperformed the best quarterly, seasonal model (i.e., QAR1 = .704). The difference between models was substantially less than those displayed by the larger firms and it was insignificant (p=.54). In general, no substantive advantage across size strata was displayed by using quarterly expectation models versus annual models, in marked contrast to previous work cited by Brown (1993).

Table 4
Pooled MAPEs of Nonseasonal Firms: Size Splits

	Small	**Medium**	**Large**
Models:			
QRWD	.726	.586	.572
QDMA1	.724	.597	.529
QAR1	.704	.536	.552
ARWD	.722	.583	.579
ADMA1	.761	.590	.497
AAR1	.686	.541	.504
Friedman S-Statistic	4.07	6.53	28.83
p-value	.54	.26	.001

Where:

QRWD = Quarterly random walk with drift model
QDMA1 = Quarterly differenced, first-order moving-average model
QAR1 = Quarterly first-order autoregressive model
ARWD = Annual random walk with drfit model
ADMA1 = Annual differenced, first-order moving-average model
AAR1 = Annual first-order autoregressive model

Table 5 presents information on how persistent the earnings series are for small, medium, and large firms. Similar to Francis et al. (2000), the autoregressive parameter in the AAR1 ARIMA model was employed as a proxy for earnings persistence. Due to stationarity and invertibility requirements in parameter estimation, the absolute value of the autoregressive parameter is bounded by 0 and 1. In this setting, a purely transitory earnings series would exhibit a value of 0 while a permanent series would exhibit a value of 1. Across all nonseasonal firms (n=167), the sample mean of the autoregressive parameter was .39, with first and third quartile values of .12 and .66, respectively.[7]

Of particular importance are the mean persistence values for small (.34), medium (.41), and large (.42) firms. The monotonic increase in persistence values across firm-size strata suggests that larger (smaller) firms' earnings series are more (less) influenced by permanent components in the earnings stream. This may provide an intuitive explanation for the impact of firm size on earnings predictions.

Table 5

Descriptive Statistics on First-Order Autoregressive Persistence Parameter
Nonseasonal Firms (n=167)

	Mean	Minimum	Q_1	Median	Q_3	Maximum
All Firms (n=167)						
	.39	-.99	.12	.34	.66	.99
Small Firms (n=56)						
	.34	-.20	.10	.33	.55	.95
Medium Firms (n=56)						
	.41	-.17	.17	.31	.69	.99
Large Firms (n=55)						
	.42	-.99	.10	.41	.89	.99

where: Q_1 = quartile one; Q_3 = quartile three

Supplementary Analyses

Several additional tests were run to assess the robustness of the reported predictive findings. First, the premier *seasonal* ARIMA models attributed to Foster (1977), Brown and Rozeff (1979), and Griffin (1977) and Watts (1975) were estimated on the *nonseasonal* sample of 167 firms. As expected, pooled MAPEs of these seasonal models computed across the original 1992-1996 holdout period were greater than the MAPE reported for the best nonseasonal model, the AAR1 model (.577).[8] The findings are qualitatively similar to those reported by Lorek and Bathke (1984). No predictive advantage is obtained during the 1992-1996 prediction interval by employing more complex *seasonal* models on firms that are characterized as *nonseasonal*.

Second, the predictive power of the six *nonseasonal* models described earlier in the paper was assessed against the premier s*easonal* ARIMA models on the *seasonal* sample of firms (n=426) across the same 1992-1996 holdout period. As expected, the best of the premier seasonal models (Foster) exhibited lower pooled MAPEs (.491) than all three of the nonseasonal quarterly models (QAR1 = .521, QRWD = .562, and QDMA1 = .501). The best of the annual nonseasonal models (ARWD), however, exhibited the smallest pooled MAPE (.484). Evidently, the advantage of employing the parsimonious nature of the ARWD model with its lack of parameter estimation was sufficient to offset the presence of seasonal effects in the data.

Finally, the inter-temporal stability of the nonseasonal models was assessed using more current data. The nonseasonal firm data bases were extended to include the next 20 quarters of data in the 1997-2001 interval. Only 101 of the original 167 nonseasonal firms had complete data over this more current time period. For this reduced sample of nonseasonal firms, the best of the nonseasonal models (ARWD) exhibited pooled MAPEs virtually identical to the best of the seasonal models (Foster) with an MAPE of .510 across the 1997-2001 prediction interval. While there was still no advantage to employing a more complex seasonal model, the relative advantage of the simpler non-seasonal models was reduced on the extended sample of nonseasonal firms (n=101).[9] Perhaps the efficacy of model structure (i.e., nonseasonal versus seasonal) is sensitive to employing predictive horizons in what may be characterized as bull markets (1992-1996) versus less robust markets (1997-2001).

Concluding Remarks

Empirical evidence that a relatively large number (n=167, i.e., 28.2%) of firms exhibit nonseasonal patterns in their quarterly earnings series is provided. Despite the presence of these firms, the financial press treats all firms as if their quarterly earnings series were purely seasonal. For example, the way in which the earnings of Tele-Communications Inc. was reported in the *Wall Street Journal* on March 25, 1996 is indicative of all such earnings disclosures:

> Tele-Communications Inc. posted a $392 million loss for the fourth Quarter, reversing a year-earlier profit…The loss compared with a Profit of $722 million in the year-earlier fourth quarter. (Emphasis Added)

In many instances, a narrative is not provided and the Digest of Earnings Reports in the *Wall Street Journal* simply portrays net income and earnings per share amounts for firms along with net income and earnings per share from the corresponding quarter of the previous year. Such disclosures place emphasis on the seasonal characteristics of quarterly earnings without providing adjacent quarter results which are more relevant benchmarks for nonseasonal firms. In a similar fashion, most academic research has failed to systematically examine the distinctive time-series properties of the quarterly earnings numbers of nonseasonal firms.

Evidence is cited that suggests analysts may fail to fully comprehend the time-series properties of earnings data. Given the relatively sophisticated screening filter that is employed to identify firms that exhibit nonseasonal quarterly earnings patterns, it is reasonable to infer that the inability to detect such atypical behavior may be an important reason for such failure. Use of quarterly ARIMA forecast models does not result in enhanced predictive performance versus annual ARIMA models on the sample of nonseasonal firms. Secondly, the size effect documented by Bathke et al. (1989) on short-term earnings forecasts also extends to long-term annual earnings forecasts. The pooled MAPEs of the best forecast model for large firms (i.e., ADMA1 = .497) are substantially smaller than the best model for small firms (i.e., AAR1 = .686). Finally, empirical evidence that the earnings size effect may be attributed to the enhanced levels of earnings persistence displayed by larger firms' earnings series versus those of smaller firms is provided.

The findings are suggestive of specific recommendations to the community of researchers and analysts interested in earnings expectations. First, researchers should not treat samples of firms as purely homogeneous. During the 1992-1996 predictive interval, nonseasonal annual ARIMA models are not dominated by seasonal quarterly ARIMA models in long-term annual earnings predictions for our sample of 167 nonseasonal firms. When the data base is extended to cover the 1997-2001 predictive interval, the relative advantage of nonseasonal modeling was reduced. However, quarterly seasonal models still did not outperform the annual nonseasonal alternatives on a reduced sample of 101 firms. This finding is particularly relevant to analysts who may wish to employ long-term earnings predictions in firm valuation settings. Second, the supplementary predictive results suggest that the choice of using nonseasonal or seasonal predictive models may be sensitive to analyzing predictive horizons in bull markets (1992-1996) versus less robust markets (1997-2001). Finally, the principle of parsimony was upheld consistently in the predictive findings for nonseasonal firms across both predictive horizons. Simpler models were not outperformed by more complex models.

Future research may be directed in several related areas to extend the analysis reported herein. ARIMA modeling assesses the output series, quarterly earnings, to determine whether statistical behavior is seasonal or nonseasonal. An alternative approach might be to examine subcomponents of the income statement such as sales and expenses to make finer distinctions between seasonal and nonseasonal effects. Perhaps examination of the factor input and product output markets of firms would help specify the underlying economic rationale for the differential time-series patterns in quarterly earnings of nonseasonal and seasonal firms. Additional work is necessary to assess the long-term, predictive ability of statistically-based earnings forecast models. Longer-term projections from such models may be the only earnings expectations available, given analysts' concentration on relatively shorter-term projections. The supplementary analysis that is reported suggests that choice of prediction models (i.e., nonseasonal versus seasonal) may be sensitive to whether earnings forecasts are generated during alternative market scenarios.

**Allen W. Bathke, Jr. is an Associate Professor of Accounting at Florida State University. He does research and teaches in the financial reporting area. **Kenneth S. Lorek is the Ralph M. Bilby Professor of Business Administration at Northern Arizona University where he teaches managerial and financial accounting. ***G. Lee Willinger is the John F. Y. Stambaugh Centennial Professor of Accounting at the University of Oklahoma where he teaches financial accounting, empirical research in accounting, and accounting theory.*

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Footnotes

[1] The singular exception is Lorek and Bathke (1984) who identify ARIMA models for nonseasonal firms.

[2] As Lorek and Bathke (1984) illustrate, use of seasonal ARIMA models on the quarterly earnings data of nonseasonal firms results in model overfitting, parameter redundancy, and lack of parsimony.

[3] Lorek and Bathke (1984) only detected 29 nonseasonal firms in their entire sample of 240 firms.

[4] See Lorek and Willinger (2003) for further discussion regarding the linkage between the abnormal earnings valuation model and long-term earnings forecasts. This work stresses that long-term annual earnings predictions (as opposed to one-year ahead annual earnings predictions) are needed by analysts to operationalize firm valuation.

[5] See Demirakos, Strong and Walker (2004) for specific evidence on valuation models that are employed by financial analysts.

[6] Conversations with representatives of First Call and Value Line underscore the unavailability of point-estimate, annual earnings forecasts beyond two-years ahead. While growth rates are provided for many covered firms, firm representatives stress that they are not designed to obtain point-estimate earnings projections. See Liu and Thomas (2000) for a discussion of this issue.

[7] The persistence values were computed using the AAR1 ARIMA model for the seasonal firms in our original sample (n=426) with a mean value of .60. The increased persistence of the seasonal firms may be attributed to the seasonal effects contained within their earnings series that were not present among the nonseasonal firms.

[8] The Foster model had a pooled MAPE of .642, the Brown and Rozeff model had a pooled MAPE of .590, and the Griffin-Watts model had a pooled MAPE of .647. Additionally, the AAR1 model provided the lowest MAPEs for each of the individual years in the predictive horizon.

[9] The relatively smaller sample of nonseasonal firms (n=101) that is examined in the supplementary analysis raises concerns of external validity. Additional research needs to be conducted to further examine the predictive power of nonseasonal versus seasonal models during both bull markets and less robust markets.