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I. Introduction

Firms that exhibit idiosyncratic nonseasonal quarterly earnings time-series properties have received considerable attention in the earnings forecasting literature. Lorek and Bathke (1984) developed a filtering mechanism that has been used to screen nonseasonal from seasonal firms to facilitate empirical analysis. Specifically, they identified a parsimonious autoregressive-integrated-moving-average (ARIMA) quarterly earnings expectation model for nonseasonal firms, a (100) X (000) model - a first-order stationary autoregressive process (i.e., AR1). They provided evidence that this *nonseasonal* model outpredicted the premier *seasonal* ARIMA models across a holdout period that included the eight quarters in the 1975-1976 interval.[1]

Subsequent work has taken these findings into account. For example, Bathke et al. (1989) controlled for the differential time-series properties of quarterly earnings by partitioning their sample of firms into nonseasonal and seasonal subsets to better assess the impact of firm size on predictive ability. More recently, Brown and Han (2000) assessed the earnings-return relationship for firms exhibiting nonseasonal quarterly earnings behavior. They employed the AR1 model as a quarterly earnings expectation model for a sample of nonseasonal firms that they identified using Lorek and Bathke's nonseasonal screening mechanism. Brown and Han tested whether the post-earnings announcement drift phenomenon may be attributed solely to the complexity of the quarterly earnings expectation model by specifically examining a set of firms (i.e., nonseasonals) whose quarterly earnings properties may be characterized as "simple." They provide empirical results consistent with the notion that the complexity of the quarterly earnings expectation model is not the underlying cause of the post-earnings announcement drift.

We agree with the strategy of identifying a quarterly earnings expectation model specifically for nonseasonal firms. ARIMA models for nonseasonal firms do not require seasonal differencing and/or seasonal autoregressive or moving-average parameters unlike the ARIMA models identified for seasonal firms. In fact, Lorek and Bathke (1984) demonstrated that the use of such complex seasonal ARIMA models for nonseasonal firms results in overdifferencing of stationary time series, parameter redundancy, and is a violation of the principle of parsimony. Brown (1993) observes that simpler quarterly earnings expectation models have proved to be more robust than more complex ones and are consistent with Occam's razor. These factors led Lorek and Bathke to model nonseasonal firms with the parsimonious AR1 process which does not rely upon differencing and/or seasonal parameters.

We extend the line of research related to the existence of nonseasonal firms for two reasons. First, the original work of Lorek and Bathke (1984) assessed whether a nonseasonal characterization of quarterly earnings was appropriate for a subsample of firms versus the seasonal characterization put forth in the literature for all firms. Lorek and Bathke recognized that most firms were seasonal and had quarterly earnings series that were well described by the seasonal quarterly earnings models identified by Brown and Rozeff (1979), Foster (1977), Griffin (1977) and Watts (1975). Their objective was not to find the "best" or "premier" nonseasonal model, but to identify a nonseasonal model that outpredicted the seasonal ARIMA models for certain types of firms (i.e., nonseasonals). Second, both Lorek and Bathke (1984) and Brown and Han (2000) used quarterly earnings data bases beginning with the early 1960s. Thomas (1993) has speculated that quarterly earnings time-series properties may have gradually changed over time. Firms may have expanded their operations (e.g., through mergers and acquisitions) or increased the number and diversity of product lines which may result in counterbalancing effects that reduce the level of seasonality across firms and produce an increase in the percentage of firms described as nonseasonal. In addition, a multitude of firm-specific, industry, and macroeconomic factors coupled with the proliferation of numerous financial accounting standards may serve to alter the income generating process of nonseasonal firms.

Rather than focusing exclusively on the AR1 process as a character -ization of nonseasonal quarterly earnings, we examine a family of nonseasonal models using current data. We assess the relative predictive ability of the candidate models and discover that nonseasonal firms are detected in greater numbers when applying Lorek and Bathke's (1984) screening filter to more current quarterly earnings data bases. The increased frequency of nonseasonal firms coupled with the lack of analyst coverage for 43.6% of our nonseasonal sample [see the Additional Analysis section] underscore the importance of looking at alternative nonseasonal quarterly earnings processes. We also present evidence on the impact of firm size on predictive ability.

Subsequent sections include a background section, and sections on the research design, including discussions of our sampling procedures, descriptive fit with respect to nonseasonal models, and predictive ability results. We end with concluding remarks, limitations and suggestions for future research.

2. Background

While we agree with the findings of previous works that have shown that a majority of firms exhibit seasonal quarterly earnings properties (Brown and Rozeff (1979) and Foster (1977), among others), our results indicate that a sizable and growing percentage of firms exhibit quarterly earnings patterns that are clearly nonseasonal in nature. The percentage and number of nonseasonal firms identified in extant work has been relatively small [i.e., 12.1% (n=29) in Lorek and Bathke (1984) and 16-18% (n=155) in Brown and Han (2000)]. We identify 35.6% (n= 296) of our sample as nonseasonal firms using Lorek and Bathke's nonseasonality screening filter. Our predictive results are supportive of an alternative nonseasonal quarterly earnings expectation model, the (010) X (000) ARIMA model, a simple random walk process [hereafter, RW].

The identification of a quarterly earnings expectation model for nonseasonal firms is of importance for several reasons. It may simply help researchers better understand the time-series properties of quarterly earnings data for different types of firms (i.e., nonseasonals versus seasonals). Such basic research, however, also has implications for other empirical-financial research topics. For example, specific knowledge of firms' earnings time-series properties has led to the development of statistical proxies for earnings persistence (Collins and Kothari (1989) and Lipe and Kormendi (1994), among others). In addition, the ability to identify better-specified quarterly earnings expectation models for nonseasonal and seasonal firms should enable researchers to more precisely disentangle the permanent and transitory earnings components that firms exhibit.[2] Such findings may also lead to more powerful tests of the relation between proxies for quarterly earnings persistence and earnings response coefficients.

The family of nonseasonal ARIMA models that we examine as possible quarterly earnings expectation models for nonseasonal firms have different valuation implications. For example, the AR1 model implies that a \$1 earnings innovation has valuation implications that are a function of the magnitude and exponential decay of its autoregressive parameter [i.e., $\acute{\emptyset}^{k} \cdot a_t$ where $\acute{\emptyset}$ = the autoregressive parameter, k = time periods in the future, and a_t is a current disturbance term]. The RW model, on the other hand, implies that a \$1 earnings innovation has a permanent valuation implication [i.e., $1 \cdot a_t$]. These models, therefore, partition earnings into different transitory versus permanent income subsets as well as having correspondingly different valuation implications.[3]

Studies like Bernard and Thomas (1990) and Brown and Han (2000) that assess the earnings-return relationship employ a quarterly earnings expectation model to differentiate between expected and unexpected earnings. Williams (1995) has argued that the choice of expectation model is important given that the likelihood of drawing erroneous inferences is influenced by the extent to which the expectation model measures the market's expectation of earnings with error. Bernard and Thomas employed a seasonal random walk model as their proxy for the unobservable market expectation of quarterly earnings. On the other hand, Brown and Han restricted their analyses to firms that exhibited nonseasonal quarterly earnings characteristics and thus employed the AR1 nonseasonal model as opposed to a seasonal model. The selection of different quarterly earnings expectation models for different types of firms is based upon the findings of studies like Lorek and Bathke (1984), among others. While we recognize that predictive ability results and capital market association tests are not perfectly correlated, Brown (1999) has suggested that advances in understanding the earnings-return relationship are more likely to follow if we abandon the myopic notion that all firms exhibit identical quarterly earnings time-series properties.[4] Finally, statistically-based quarterly earnings expectation models must be used for 43.6% of our nonseasonal sample given the lack of analyst coverage for such firms. Evidence with respect to the most accurate statistically-based quarterly earnings model for uncovered firms is particularly salient to researchers seeking accurate quarterly earnings predictions.

3. Research Design

Data Sampling Procedures

We obtained a sample of 831 calendar, year-end firms that had complete time-series data on quarterly net income before extraordinary items for each quarter during the 1984 to 2003 interval on the Quarterly Compustat tapes. To partition our sample with respect to nonseasonality of the quarterly earnings stream, we computed sample autocorrelation functions (SACFs) of the quarterly earnings series for each firm using the first 40 observations in the data base (1984-1993).[5] We employed the same nonseasonality screening filter originally developed by Lorek and Bathke (1984) to determine those firms in the 831 firm sample that exhibited nonseasonal quarterly earnings characteristics. Specifically, a firm was designated 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.[6] This resulted in our classifying 296 of 831 (35.6%) sample firms as nonseasonal.

Profile Information on Sample Firms

Table 1 presents profile information on the nonseasonal (n=296) and seasonal (n=535) test samples.[7] We report mean (median) values for total assets as of December 31, 1993 as well as annual income and sales, both computed for the last year of the identification period (1993). The number of loss quarters pertains to the 40 quarter interval encompassing the 1984-1993 identification period.

Table 1
Profile Information on Sample Firms

	Nonseasonals			Seasonals		
	Mean		**Median**	**Mean**		**Median**
Total Assets	$7,922.1		$996.5	$7,050.1		$1,016.7
(in $ millions		n=293			n=527	
as of 12/31/93)			p = .789*			
Annual Income	$95.1		$12.0	$198.6		$33.7
(in $ millions		n=296			n=535	
FYE 1993)			p= .003*			
Annual Sales	$2,934.2		$622.8	$3,455.2		$653.0
(in $ millions		n=283			n=527	
FYE 1993)			p= .610*			
# Of Loss Qtrs.	6.70		3	4.77		1
(during ident.		n=296			n=535	
Period 1984-93)			p= .001*			

***** based upon Mann-Whitney U-tests.

The nonseasonal firms exhibit mean (median) total assets of $7,922.1($996.5) million versus $7,050.1 ($1,016.7) million for seasonal firms. However, Mann-Whitney U-tests revealed insignificant differences (p= .789) in total assets and annual sales (p= .610) across samples. Seasonal firms, however, were significantly more profitable (p= .003). Specifically, 1993 mean (median) annual income numbers were $198.6 ($33.7) million for the seasonals versus $95.1 ($12.0) million for the nonseasonals.

We also provide mean (median) number of loss quarters experienced by sample firms throughout the 40 quarter model identification period (1984-1993). Differences in the frequency of loss quarters between seasonal and nonseasonal firms may be partially responsible for the diversity in quarterly earnings time-series properties of these firms. Nonseasonal firms experienced significantly greater loss quarters with mean (median) losses of 6.70 (3) versus 4.77 (1) for seasonals (p=.001). These descriptive findings are suggestive of potentially reduced levels of autocorrelation in the quarterly earnings streams of nonseasonals vis-à-vis seasonals. Additionally, Hayn (1995) provides evidence that losses are less informative than profits about firms' future prospects due to the liquidation option that shareholders possess.

Modeling Considerations

Table 2 displays the cross-sectional SACFs for the undifferenced (d=D=0), consecutively-differenced (d=1, D=0), seasonally-differenced (d=0, D=1) as well as consecutively and seasonally-differenced (d=1, D=1) quarterly earnings series for the 296 nonseasonal firm sample. The patterns in the spikes of these respective SACFs provide clues with respect to the (pdq) X (PDQ) ARIMA structures that might be appropriate for nonseasonal firms.

Table 2
Cross-sectional Sample Autocorrelation Function
For the 296 Nonseasonal Firms: 1984 – 1993
Means and Standard Deviations

d D	1	2	3	4	5	6	7	8	9	10	11	12
0 0												
mean	.273	.217	.170	.153	.099	.061	.042	.035	.005	-.019	-.027	-.044
sd	(.158)	(.179)	(.192)	(.199)	(.205)	(.209)	(.213)	(.215)	(.217)	(.219)	(.220)	(.222)

d D	1	2	3	4	5	6	7	8	9	10	11	12
1 0												
mean	-.399	-.019	-.014	.029	-.016	-.011	-.006	.016	-.008	-.014	.008	-.002
sd	(.160)	(.187)	(.191)	(.193)	(.194)	(.196)	(.198)	(.200)	(.201)	(.202)	(.204)	(.205)

d D	1	2	3	4	5	6	7	8	9	10	11	12
0 1												
mean	.159	.096	.034	-.332	-.023	-.021	-.020	-.009	-.011	-.021	-.023	.045
sd	(.167)	(.178)	(.182)	(.186)	(.207)	(.209)	(.212)	(.214)	(.215)	(.217)	(.219)	(.220)

d D	1	2	3	4	5	6	7	8	9	10	11	12
1 1												
mean	-.389	-.002	.177	-.391	.151	.002	-.002	.001	.004	-.004	.011	-.019
sd	(.169)	(.197)	(.198)	(.206)	(.229)	(.234)	(.236)	(.238)	(.240)	(.241)	(.243)	(.245)

where: d = consecutive differencing
D = seasonal differencing

Lorek and Bathke (1984) identified the (100) X (000) AR1 model by examining the SACF of the undifferenced (d=D=0) quarterly earnings series for their sample of 29 nonseasonal firms. Close inspection of the undifferenced series in Table 2 reveals the nonseasonal nature of the quarterly earnings series in our sample of firms since there are no spikes at the seasonal lags of 4, 8, and 12 (.153, .035, and -.044, respectively). The SACF of the undifferenced series depicts a monotonic pattern of consecutively declining values across the first four lags (.273, .217, .170, .153) suggestive of an AR1 process.[8] Thus, the AR1 model is still a plausible description of the quarterly earnings series of nonseasonal firms. While this pattern was evident in Lorek and Bathke, the values they report across the same lags were markedly higher (.546, .460, .348, .270). This provides a descriptive clue that the AR1 model might not perform as well on our nonseasonal sample given the substantially reduced levels of autocorrelation that are evident.

Inspection of the consecutively-differenced (d=1, D=0) series in Table 2, reveals behavior consistent with an (011) X (000) integrated-moving-average ARIMA process [hereafter, IMA]. Lags 2-12 exhibit relatively low levels of autocorrelation with SACF autocorrelation values insignificantly different from zero. The presence of a spike at lag one (-.399) is suggestive of a first-order moving-average parameter in the tentative model. This leads to the specification of the IMA ARIMA model as the second candidate quarterly earnings expectation model for our family of nonseasonal models. Further examination of the autocorrelation of the residuals [unreported] of the IMA process reveals the possible presence of an autoregressive pattern. Therefore, we modified the IMA process by inserting a first-order autoregressive parameter resulting in a (111) X (000) (hereafter FIMA) ARIMA model - our third candidate nonseasonal model.

We also included the random walk model (i.e., RW), a (010) X (000) ARIMA process.[9] This model avoids all parameter estimation and simply extrapolates the most recent change in quarterly earnings into the future. To the extent that the income-generating process has become more volatile through time, the RW model may prove to be more robust than the other candidate nonseasonal models that require estimation of regular autoregressive and/or moving-average parameters. Examination of the RW model is consistent with the viewpoints on parsimony expressed above by Brown (1993) and Thomas (1993), among others. Therefore, we include the RW model as the fourth candidate nonseasonal model. These four expectation models represent a family of nonseasonal models exhibiting varying degrees of parsimony.

We compare the predictive ability of the four nonseasonal models discussed above versus the BR seasonal ARIMA model: (100) X (011).[10] Lorek and Bathke (1984) provided evidence that the AR1 model significantly outperformed the seasonal premier ARIMA models in one-step-ahead quarterly earnings predictions across the eight quarter holdout period in 1975-1976. We reassess the predictive performance of the AR1 process versus the BR ARIMA model and competing nonseasonal structures (i.e., IMA, FIMA, and RW), using a more extensive and recent holdout testing period (i.e., the forty quarters in 1994-2003) as well as a larger sample of nonseasonal firms (n=296). These methodological refinements that we incorporate should serve to enhance the external validity of our findings.

The parameters of the five expectation models were estimated using a quarterly earnings data base beginning with the first quarter 1984 and ending with the fourth quarter 1993. These models were used to generate the first quarter 1994 predictions. The parameters were reestimated prior to making each additional one-step-ahead prediction over the 1994-2003 period. Therefore, the forecast profile contains forty one-step-ahead quarterly earnings forecasts for each of the five expectation models. That is, the nonseasonal sample of 296 firms yields 11,840 firm/quarter forecasts.

The accuracy of the forecasts was assessed using the absolute percentage error metric (APE): $[\,|(A - F) / A|\,]$ where A = actual quarterly earnings and F = forecasted quarterly earnings. Median APEs (i.e., MAPEs) are reported in panel A of Table 2 for the one-step-ahead quarterly earnings predictions across the five expectation models (AR1, IMA, FIMA, RW, and BR) for each individual quarter (1st, 2nd, 3rd, 4th) as well as on a pooled basis across all quarters and years.[11] The accuracy of the predictions was assessed by using the Friedman ANOVA ranks test (Hollander and Wolfe 1973). For each firm/quarter observation, the prediction model yielding the smallest APE 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 five. Panel A also provides the average rank of each prediction model and Friedman's S-statistic and its associated level of significance for each individual quarter and on a pooled basis across quarters and years.

Table 3
Median Absolute Percentage Errors of One-Step-Ahead Quarterly Earnings Predictions (1994-2003) (n=296)

Panel A: Overall Results

Model	1st Qtr Avg Rank	1st Qtr MAPE	2nd Qtr Avg Rank	2nd Qtr MAPE	3rd Qtr Avg Rank	3rd Qtr MAPE	4th Qtr Avg Rank	4th Qtr MAPE	Pooled Avg Rank	Pooled MAPE
AR1	3.34	.480	3.52	.458	3.46	.458	3.37	.522	3.42	.478
IMA	2.84	.388	2.90	.356	2.92	.363	2.85	.420	2.88	.380
FIMA	2.89	.406	2.96	.374	2.93	.372	2.88	.445	2.91	.396
RW	3.05	.449	2.62	.300	2.56	.284	2.62	.366	2.71	.344
BR	2.87	.381	3.00	.370	3.14	.390	3.27	.566	3.07	.420
Friedman ANOVA S-statistic	202.83		511.14		519.29		468.53		1,378.54	
Significance Level	.001		.001		.001		.001		.0001	

where:

AR1 = (100) X (000) ARIMA model
IMA = (011) X (000) ARIMA model
FIMA = (111) X (000) ARIMA model
RW = (010) X (000) ARIMA model
BR = (100) X (011) ARIMA model

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

Model (Average rank)	IMA 2.88	FIMA 2.91	RW 2.71	BR 3.07
ARI (3.42)	IMA***	FIMA***	RW***	BR***
IMA (2.88)		IMA**	RW***	IMA***
FIMA (2.91)			RW***	FIMA***
RW (2.71)				RW***

where:

*** = significant at .001
** = significant at .01

Inspection of the results presented in panel A of Table 3 reveals the following: First, the RW model provides the lowest pooled MAPE across quarters and years (.344) as well as the lowest MAPE for quarters two (.300), three (.284) and four (.366). The BR model provides the lowest MAPE (.381) for quarter one. Second, the RW model provides the lowest average rank among the five expectation models for the same periods where it exhibits the lowest MAPEs. Third, the AR1 model provides the highest pooled MAPE (.478) and the highest pooled rank (3.42). These results underscore the importance of our findings. Although the descriptive fit of the AR1 model is still adequate for nonseasonal firms, other more parsimonious nonseasonal models exhibit significantly greater predictive power.

Panel A of Table 3 also reveals a statistically significant difference in the average ranks of the MAPEs (p=.001) for each individual quarter in addition to the pooled results across quarters and years (p=.0001). Panel B provides all pairwise comparisons between each of the prediction models using the pooled predictions.[12] Recall that lower rankings imply a lower MAPE and greater predictive ability. Each cell value in Panel B contains the superior prediction model for the row-column comparison as well as its corresponding significance level. Specifically, the RW model outperforms the AR1, IMA, FIMA, and BR ARIMA model at p=.001. The statistical dominance of the RW model over all other candidate models in the pooled predictions is suggestive of the need to employ the RW model as a quarterly earnings expectation model for nonseasonal firms when using more current data. Panel B also reveals that the AR1 model is outperformed by all other models (p=.001). This finding underscores the reduced predictive power of the AR1 process for nonseasonal firms. Finally, as expected, the IMA and FIMA models significantly outperform the BR ARIMA model (p=.001).

While the pooled results (as well as the unreported predictive results for the second, third, and fourth quarters) consistently support the predictive dominance of the RW model, the results for quarter one are less straightforward. The best performing model in terms of ranks is the IMA model (2.84) while the BR model provides the lowest MAPE (.381). Since the conditioning quarter for the RW model is the most recent quarter, the RW expectations for the first quarter are based entirely upon the fourth quarter results in the previous year. Bathke and Lorek (1984), among others, provide results consistent with fourth quarter earnings that are heavily influenced by the "settling-up" effect where annual accruals are brought into correspondence with quarterly estimates. This source of measurement error in fourth quarter earnings numbers may serve to mitigate the relative predictive power of the RW model on first quarter extrapolations as this model relies exclusively on the fourth quarter of the prior year as a prediction of earnings for the first quarter of the current year.

The dominance (inferiority) of the RW (AR1) model was not time-period specific. Analysis [unreported] of individual years in the 10-year holdout period reveals that the RW model provided the lowest MAPEs for 8 of 10 years, the only exceptions were 2001 and 2002. The AR1 model, however, provided the highest MAPEs for each of the 10 years in the holdout period demonstrating its relatively poor predictive power across the entire decade that we examine.

4. Additional Analysis

Bathke et al. (1989) provide evidence that firm size affects the predictive accuracy of statistically-based, *seasonal* ARIMA quarterly earnings expectation models (i.e., BR, F, and GW). The sample of nonseasonal firms that we examine exhibit radically different quarterly earnings time-series properties that are at variance with the seasonal ARIMA models. Nonseasonal ARIMA models do not employ seasonal autoregressive or moving average parameters and/or seasonal differencing that are commonly used in the seasonal ARIMA models. We were, therefore, interested in assessing the effect, if any, that firm size might have on the predictive power of the more parsimonious, nonseasonal quarterly earnings expectation models.

We partitioned our sample of nonseasonal firms into small (n=98), medium (n=98) and large (n=97) firm subsets on the basis of total assets measured at the end of the model identification period, December 31, 1993.[13] We generated one-step-ahead quarterly earnings predictions across the 40 observation holdout period (i.e., 1994-2003) using the RW model. Pooled MAPEs for the small (.402), medium (.410), and large firm subsets (.225) were significantly different (p=.0001) based upon the K-sample median test. Mann-Whitney U-tests of paired comparisons revealed that large firm predictions were significantly smaller than those generated by both small and medium-size firms (p=.0001). However, there were no significant differences in the accuracy of the predictions for the small versus medium firm comparisons (p=.958). These results clearly demonstrate the existence of a firm-size effect on the quarterly earnings predictions of the RW model for nonseasonal firms. Researchers who employ research designs that are sensitive to the accuracy of quarterly earnings expectations for nonseasonal firms should consider controlling for this firm-size effect.

We also provide evidence on whether the nonseasonal sample firms were covered by security analysts as reported by *I/B/E/S* at the end of the model identification period (i.e., December 31, 1993). We find that 129 of 296 sample firms (43.6%) had no analyst coverage. For such firms, knowledge of the superior predictive power of the RW model takes on added importance and is particularly salient information for researchers who must rely exclusively on statistically-based quarterly earnings expectation models for uncovered firms. For example, we observe a significant decline in predictive power in the pooled MAPEs of the AR1 model (.478) versus the RW model (.344) as reported in Table 3.

Since 43.6% of the nonseasonal sample firms have no analyst coverage, empirical evidence on the incremental predictive power of the RW model on covered versus uncovered firms is also of potential interest. Recent evidence by Elgers, Lo, and Pfeiffer (2001) suggests that analyst following is positively associated with the efficiency with which investors process firm-specific information. Moreover, analysts may decide to cover certain firms that exhibit quarterly earnings time-series properties more conducive to statistical extrapolation. We generated pooled one-step-ahead quarterly earnings predictions across the 1994-2003 holdout period for the covered (n=167) and uncovered (n=129) firms separately. MAPEs for the covered (uncovered) firms were .302 (.392), respectively. Mann-Whitney U-tests revealed significantly smaller MAPEs for the covered firms (p=.0001). We hypothesize that the time-series forecasts of covered firms, in addition to being significantly more accurate, might be combined more readily with firm-specific, industry, and macroeconomic information resulting in a decision by analysts to cover such firms. Alternatively, earnings series of covered firms may be more persistent. Additional research is necessary to fully examine these issues.

5. Concluding Remarks

While we present empirical results supportive of the superior predictive power of the RW model for quarterly earnings predictions of nonseasonal firms, there are at least two potential limitations pertaining to our research design. First, our sampling procedures operationalized across the 1984-2003 time period are subject to a survivorship bias endemic to all time-series work. Second, while we have examined a very wide set of nonseasonal ARIMA models (i.e., AR1, IMA, FIMA, and RW), other nonseasonal expectation models could yield different results. Nevertheless, the relatively large number of nonseasonal firms that we identify (n=296), especially relative to extant work, serves to mitigate against the impact of these limitations.

We provide new empirical evidence that the number of nonseasonal firms is increasing in frequency relative to the studies performed by Lorek and Bathke (1984) and Brown and Han (2000). Heretofore, the AR1 model was the accepted quarterly earnings expectation model for nonseasonal firms. Our results suggest that the RW model provides significantly more accurate pooled one-step ahead quarterly earnings predictions across the 1994-2003 holdout period. In fact, the AR1 model was the *worst* performing expectation model across quarters, years, and on a pooled basis. We attribute the poor performance of the AR1 model in our study to at least two factors: 1) the reduced levels of autocorrelation evidenced in the SACFs based on the more current data that we examine relative to the SACFs examined by Lorek and Bathke (1984) who used less current data, and 2) the significantly greater frequency of loss quarters evidenced by nonseasonal versus seasonal firms during the model identification period. These factors favor the more parsimonious RW model versus more complex alternatives.

We also document that 129 of 296 sample firms (43.6%) had no analyst coverage at the end of the model identification period. Researchers interested in performing earnings-return analyses for uncovered firms exhibiting nonseasonal quarterly earnings characteristics must rely exclusively upon statistically-based models for such firms. Our results suggest that researchers who employ the RW model for nonseasonal firms will be able to separate expected from unexpected earnings with greater precision than relying upon the AR1 model. Finally, we provide new evidence of a firm-size predictive effect for nonseasonal firms, consistent with the findings of seasonal firms, where the earnings predictions of larger firms derived from the RW model are significantly more accurate than those of smaller firms.

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Endnotes

[1] In customary (pdq) X (PDQ) notation, these include the Foster (1977) (100) X (010) with drift model [hereafter F], the (011) X (011) Griffin (1977) and Watts (1975) model [hereafter GW], and the Brown and Rozeff (1979) (100) X (011) model [hereafter BR].

[2] See Baginski et al. (1999) for an example of a study that combines ARIMA models for earnings data with valuation theory to specify a statistical proxy for earnings persistence.

[3] See Collins and Kothari (1989) for additional discussion on valuation implications of different time-series models for earnings.

[4] O'Brien (1988) found a stronger association between abnormal returns and ARIMA models than analyst eps forecasts taken from the *Institutional Brokers' Estimate System* [I/B/E/S]. See Brown (1993) for an extensive discussion regarding the mixed evidence researchers have found with respect to the dual evaluative criteria of predictive ability and capital market association.

[5] We withheld the last 40 observations of quarterly earnings (1994-2003) as a holdout period for predictive assessment.

[6] This procedure was conducted on the consecutively-differenced series to avoid potential nonstationarity problems.

[7] Annual income and number of loss quarter statistics are based upon the full sample of nonseasonals (n=296) and seasonals (n=535). Total asset and annual sales statistics were based on a slightly smaller numbers of firms due to missing data.

[8] We suppress presentation of the partial autocorrelation function for brevity, but it does reveal a spike at the first lag (.273) with behavior consistent with a white-noise series across the remaining lags of the SACF. This provides corroborative descriptive evidence supportive of the AR1 process.

[9] While the RW process has not fared well in predictive ability assessments using *quarterly* earnings numbers, Albrect, Lookabill and McKeown (1977) and Watts and Leftwich (1977) provide evidence that it outperforms seasonal ARIMA models using *annual* earnings data bases.

[10] We suppress providing detailed predictive results for the F and GW ARIMA models. The BR model provides significantly more accurate pooled one-step-ahead quarterly earnings predictions than the GW model and provides predictions virtually indistinguishable from those of the F model.

[11] We report median rather than mean APEs across sample firms to mitigate against the effect of explosive errors. Mean APEs using a 100% truncation rule provide qualitatively similar results to those that we report.

[12] Analysis of the second, third, and fourth quarter predictions yields results qualitatively similar to the pooled predictive results.

[13] We lost 3 of 296 firms due to unavailability of total asset data. Attempts to partition our sample using the fair market value of common stock equity resulted in considerably more missing data.