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George Foster

ABSTRACT: The time-series behavior of the quarterly earnings, sales and expense series of 69 firms over the 1946–74 period is examined. A Box-Jenkins time-series methodology is adopted. Based on inspection of the cross-sectional autocorrelation function, it is concluded that each series has (a) an adjacent quarter-to-quarter component and (b) a seasonal component. One-step-ahead forecasting results reveal that these two components can be successfully modelled at the individual firm level. The use of various quarterly forecasting models in security price analysis is also examined. The results are consistent with the market adjusting for seasonality in quarterly earnings in interpreting each quarter's earnings change.

INCREASING attention is being given to the time-series properties of quarterly accounting data. This attention is related to both (1) the importance of research on quarterly accounting issues and (2) the importance of time-series research in accounting and finance. This paper provides evidence on the time-series behavior (via the Box-Jenkins (B-J) methodology) of the quarterly earnings, sales and expense series. It also examines the "predictive ability" of Box-Jenkins forecasting models vis-a-vis the forecasting models used in previous studies on the information content of quarterly data. Predictive ability will be examined in two contexts: (1) first, the ability to forecast future values of the same series and (2) second, the ability to approximate the capital market's expectation model when examining the market's reaction to accounting data. This time-series and predictive-ability analysis has relevance to the interim accounting issues currently being considered by the Financial Accounting Standards Board (FASB).

TIME-SERIES RESEARCH

Time-series evidence is important to both general research issues in accounting and finance and specific research issues in interim reporting.

Time-Series Research in Accounting and Finance

Time-series research is important to several areas of accounting and finance. One such area is the "smoothing litera-

The comments of S. Albrecht, W. Beaver, P. Brown, N. Gonedes, P. Griffin, J. King, H. Nurnberg and R. Watts and the participants of a Stanford Workshop (December 1975) and an Ohio State Workshop (April 1976) are appreciated.

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ture." The importance of management knowing the stochastic process generating the reported accounting series when making "smoothing" decisions is well-documented in Gonedes [1972]. Indeed, he shows that for some time-series processes, attempts to smooth the basic series may increase the variance of the reported series. Another area using the results of time-series analysis is the security valuation literature in which issues such as estimation of the cost of capital, the importance of dividend policy and the association of alternative earnings measures have been examined [Miller and Modigliani, 1966; Foster, 1976a]. In many of these studies an estimate of the expected earnings of firms is based on the past earnings series. In this context, knowledge of a descriptively valid time-series model of earnings is critical in determining the weights to be placed on each past period's earnings. Another area using time-series results is the accounting information/capital markets literature. The results of studies, e.g., Brown and Kennelly (B-K) [1972] and Foster [1973], are conditional upon the expectation model examined. Choice of an inappropriate model (one inconsistent with the time series) may lead to erroneous inferences about the information content of accounting data.

Time-Series Research and Interim Reporting

The Financial Accounting Standards Board, in announcing the addition of the interim reporting project to its technical agenda, noted:

> The project will address the question of whether an interim financial reporting period should be considered as a discrete period that stands alone or as an integral part of the annual reporting period. . . . This question is particularly important to companies in industries having seasonal operations. [1975, p. 1]

One reporting alternative that the FASB presumably will consider is requiring companies having seasonal operations to report seasonally adjusted quarterly data. At present, a variety of adjustment techniques have been proposed. Time-series analysis provides important information for evaluating these techniques for seasonally adjusting quarterly earnings. This statement is based on the assumption that *it is necessary to know something about the unadjusted series before deciding on the set of techniques to produce the seasonally adjusted series.* Note also that several of the proposed seasonal adjustment techniques require forecasts of future sales, e.g., Green [1964]. A forecast requires a model for the behavior of the series, and the results of time-series analysis provide one basis for selecting such a model. The analysis in this paper provides evidence on this model choice issue.

Another interim issue examined is whether the aggregate market, when interpreting an interim report, adjusts for seasonality in the earnings series. One argument that industry officials have advanced against extensive interim disclosure rules is that investors would be "confused" or "misled" by the interim results of seasonal firms. The following two industry statements, taken from Taylor [1963, p. 133], are illustrative of this concern:

> Instead of clarifying the picture, the issuance of a semi-annual report by this company would serve to confuse those dealing in Brown-Forman issues. This is because our business is highly seasonal in nature.
>
> The greater part of our sales volume is transacted in the closing months of the calendar year which is also our fiscal year. Our company has in the past only been able to ascertain its financial position for the year during the months of November and December when the greatest volume of sales and deliveries occur. A report filed during the

> summer might only provide investors and prospective investors with information which might be misleading or subject to misinterpretation, notwithstanding any qualifying statements submitted by management.

Are these statements descriptively valid at the aggregate market level? Evidence on this issue is presented in this paper.

Prior Evidence on Quarterly Time Series

Evidence on the time-series behavior of quarterly earnings, and to a lesser extent quarterly sales, is available from many of the empirical studies using quarterly data. No detailed evidence on the time-series behavior of the quarterly expense series is known. Appendix B of a previous version of this article [Foster, 1976] contained a "reasonably comprehensive" bibliography of this literature—seventy-one empirical studies using quarterly accounting data are referenced. In this section, the results of three studies utilizing the Box-Jenkins methodology with quarterly accounting data are discussed.

The time-series properties of quarterly earnings were examined in Lorek, McDonald and Patz [1976]. Box-Jenkins models were fitted to individual firms with thirty-two to fifty-two quarterly earnings observations. They noted the "pervasive importance of seasonality in the models. Thirty-five of the forty time series analyzed required either seasonal parameters or seasonal differencing of the data" [p. 328]. A more detailed analysis of the time-series of quarterly earnings was presented in Watts [1975]. The sample contained 175 firms with data bases for individual companies varying from 18 to 50 observations. The serial correlation of forecast errors from a variety of expectation models was examined. Watts [1975] reported (1) strong evidence of seasonality in quarterly earnings and (2) "evidence that adjacent quarterly earnings changes are not independent but are related" [p. 9].

Griffin [1976] reached similar conclusions as Watts. His sample contained ninety-four firms over the 1958–71 period. Based on cross-sectional autocorrelation and partial autocorrelation functions, he suggested, "the behavior of quarterly earnings might be characterized as a first order autoregressive process in fourth differences" [p. 19]. He also suggested the alternative characterization of a "first order moving average process . . . in the first differences" [p. 19].

Identification and Estimation Issues

Identification and estimation of Box-Jenkins models for quarterly earnings involve certain issues that have been given scant attention in prior accounting studies. First is the issue of the number of observations required in Box-Jenkins analysis. For example, Kaplan [1975] argued that "Box-Jenkins analysis requires an enormous amount of data to estimate the underlying process which presumably is remaining stationary during this time" [p. 35]. Not one reference was given to support this assertion.

Note that in the absence of structural change, the more observations one has, the greater is one's ability to identify the underlying model. However, a key issue when using finite samples is the small sample properties of the estimators of B-J models. The statistical literature has not examined this issue extensively for many specific B-J models. The A.R.(1) and M.A.(1) models have been examined in most detail. Nelson [1974], for instance, examined via simulation the identification and estimation of M.A.(1) models with sample sizes of 30 and 100. His results suggest that the problem of identifying M.A.(1) models with θ_1 in the .1 to .5 range are much more severe with samples of 30 than with samples of 100 observations. Nelson's results relate to nonseasonal models. There is even less evidence on the small sample properties of the estimators of seasonal Box-Jenkins models.[1]

One factor illustrated by Nelson [1974] is the potential to identify tentatively a diversity of models across firms when using finite samples, even when all firms have the same underlying time-series. Nelson [1973, Ch. 5] presented some further evidence on this issue. One approach to checking for this possibility is to examine the predictive ability of the fitted models on a set of data which are *not* used to identify them. Watts [1970] provided interesting evidence on this issue. When Watts estimated Box-Jenkins models for their annual earnings series (unadjusted available for common) over the 1927–64 period, he found considerable diversity across thirty-two firms. However, when he used the fitted models to predict earnings in the 1965–68 period, they performed approximately the same as a model assuming that the earnings of all firms follow a random walk. One explanation consistent with this result is that all firms have the same underlying time series and that the observed diversity in fitted models across firms is a sampling phenomenon. This issue also will be examined in this paper.

Another important issue in time-series analysis is the ability to discriminate among alternative models on the basis of finite samples. Gonedes and Roberts [1976] examined this issue for the A.R.(1) model. They specify the underlying model to be:

$$\tilde{y}_t = \beta_1 \tilde{y}_{t-1} + \tilde{\varepsilon}_t. \qquad (1)$$

Based on extensive simulation analysis, they show that an "incorrect model" (a random walk model) can lead to lower mean square error predictions than the A.R.(1) model when β_1 is estimated from a finite sample. This result was for β_1 prespecified at .99, .95, .90 and .70 for samples of 20 and 30 and for β_1 prespecified at .99, .95 and .90 for samples of 60. There are no similar extensive results known for more complex Box-Jenkins models. One inference from Gonedes-Roberts is that if there is concern with forecasting performance, then parsimonious models *may* perform very well, even though they may be an "incorrect" description of the underlying time-series. In a small sample, it may not be possible to identify and estimate efficiently the "correct" underlying model. The forecasting performance of several reasonably parsimonious models used in this paper vis-a-vis models requiring estimation of more parameters should provide some additional evidence on this issue.

The problem of firms structurally changing over time also needs further consideration. The Box-Jenkins methodology assumed that the series is a homogeneous stationary one. Yet, over time, firms may change their lines of business or may merge with other firms. Similarly, the competitive conditions in a firm's input and output markets also may change. All such changes can result in changes in the time-series model of a firm's earnings, its sales or its expenses. In this article, the stability issue and its effect on predictive performance also will be considered.

Alternative Models for Forecasting Quarterly Accounting Series

The class of forecasting models to be examined is those restricted to the past sequence of quarterly earnings, sales and expenses. Brown and Kennelly (B-K) [1972] examined two such models in their study of the information content of quarterly earnings.

[1] Cleveland [1972] has provided simulation evidence about the effect on the sample autocorrelation function when only one of four quarters has a marked seasonal pattern; see also Froeschle [1975].

Model 1: $E(Q_t) = Q_{t-4}$ (2)

Model 2: $E(Q_t) = Q_{t-4} + \delta$ (3)

where Q_t = earnings in quarter t of a given year and δ is a drift term. The drift term in B-K [1972] was "the average change in that quarter which has occurred over the available history" [p. 407]. Both models were applied to the earnings series of all companies. The B-K sample included ninety-four Compustat firms—the period of stock market analysis was 1958–67. The API for Model 2 exceeded that for Model 1 in three of the four quarters—however, the difference between the two did not appear to be large.

Models 1 and 2 assume a seasonal pattern in quarterly earnings. A set of models which ignore any such seasonality are used in studies on the information content of annual earnings. Two such non-seasonal models are:

Model 3: $E(Q_t) = Q_{t-1}$ (4)

Model 4: $E(Q_t) = Q_{t-1} + \delta.$ (5)

Whether any seasonality exists in quarterly accounting data is obviously an empirical question. Models 3 and 4 provide some insight into the consequences of suppressing any seasonality in quarterly data. (Note that δ in Model 4 is calculated using only annual data.)

Beaver [1974] used the seasonal Model 2 in examining the information content of the magnitude of unexpected earnings. The drift term was modified slightly to that used by B-K [1972]; the data base was the B-K base using only the 1958–65 period. Beaver noted one important misspecification with Model 2—"the quarterly forecast errors possess [a] significant positive [first order] serial correlation [of] .416" [p. 7]. This positive serial correlation implies that there is some systematic pattern in the past series not being exploited in forecasting future values. This result is consistent with the Watts [1975] and Griffin [1976] findings that adjacent quarterly earnings are not independent.

One approach to the misspecification problem would be to retain the basic features of Model 2 and assume that the autocorrelation follows a first-order autoregressive process. Let

$$W_t = Q_t - Q_{t-4}. \tag{6}$$

The adjustment to Model 2 becomes:

$$W_t = \phi_1 W_{t-1} + \delta. \tag{7}$$

The model in (7) is an A.R.(1) in the seasonally differenced series in the terminology of Box-Jenkins [1970]. For this model, a preliminary estimate of ϕ_1 is given by the first order autocorrelation coefficient (r_1); a preliminary estimate of δ is given by $(1-\phi_1)\cdot u$, where u is the mean of the seasonally differenced series. For predicting the levels of quarterly series, (7) becomes:

Model 5:

$$E(Q_t) = Q_{t-4} + \phi_1(Q_{t-1} - Q_{t-5}) + \delta. \tag{8}$$

The main potential defect of Model 5 is the assumption that an A.R.(1) process describes the time-series behavior of the fourth differences in quarterly data of *all firms*. This assumption is obviously a very strong one.

An alternative approach is to utilize the Box-Jenkins [1970] methodology for identifying the process generating *each individual firm's* data. Expositions of this methodology are available in Box-Jenkins [1970] and Nelson [1973].[2]

[2] Applications of the methodology to seasonal time series analysis include Thompson and Tiao [1971], Chatfield and Prothero [1973] and Sullivan and Marcis [1975]. The Chatfield and Prothero article (and the subsequent comments in the same issue by Wilson and Harrison) is a good account of the problems in identifying Box-Jenkins seasonal models; see also Box and Jenkins [1973].

Briefly, there is a three-step approach to modelling the time series of each firm. The first step is model identification. This involves, among other things, a comparison of the sample autocorrelations and partial autocorrelations with theoretical patterns of particular autoregressive-moving average models. The second step is model estimation. The parameters of the model are estimated via a nonlinear estimation procedure.[3] The final step is diagnostic checking. For instance, the residuals from the identified model are examined to see if they are serially uncorrelated. A Box-Jenkins model will be identified for each firm for each of the earnings, sales and expense series. This model—termed Model 6—is another alternative model for forecasting quarterly accounting data.

Note that Models 5 and 6 are Box-Jenkins models of a quarterly series. Model 5 is a reasonably parsimonious model—it requires estimation of only ϕ_1 and a drift term. Using the Box-Jenkins notation for multiplicative seasonal models, it is a $(1, 0, 0) \times (0, 1, 0)_{s=4}$ model. Note, however, that this specific model does not involve multiplicative terms. Model 6 is the result of a more extensive analysis of each firm's sample autocorrelation and partial autocorrelation functions. Even though we restrict the number of parameters estimated, more firm-specific parameters generally will be recognized than for Model 5. One potential limitation of the more extensive analysis for Model 6 is the possibility of search bias. That is, sampling variation in a finite sample may lead to the tentative identification of a model which is not representative of the underlying time-series. Some insight into this possible search bias will be gained by examining the predictive ability of Models 5 and 6 on a set of observations *not* used for model identification and estimation.

Sample of Firms

The firms included in the sample had to meet three criteria:

1. Quarterly earnings (after tax but before dividends) and quarterly sales available for the 1946–74 period. Data for the 1946–61 period were taken from various Moody's manuals (Industrials, Transportation, etc.). Data for the 1962–74 period were taken from the Compustat file.
2. Daily security returns available on the CRSP daily return tape for the 1962, 6-1975, 6 period, and
3. Quarterly earnings/sales announcements for the 1962–74 period reported in the *Wall Street Journal Index*.

Sixty-nine firms met these criteria. The most stringent criterion was (1). Over this entire period, the New York Stock Exchange recommended (but did not require) quarterly reporting of sales. Neither the SEC nor the accounting profession required reporting of *both* sales and earnings over the entire 1946–74 period.[4] Thus, the sample is not a random one as regards the reporting of quarterly information. The sample also has the familiar "survivorship" bias because it includes only those firms which have existed for at least 29 years. It is important to note that inferences drawn from

[3] The Box-Jenkins programs used in this research were developed by Charles Nelson. The "ESTIMATE" program is described as follows:

> The estimates provided by the program are those which minimize the unconditional sum of squares function through "backforecasting" of pre-sample observations. The minimum is located by use of Marquardt's iterative procedure which amounts to a compromise between the methods of Gauss-Newton and steepest descent [Nelson, 1975b, p. 6].

[4] Taylor [1963] and Edwards, Dominiak and Hedges [1972] provided background details on institutional changes in interim reporting requirements.

TABLE 1

S.I.C. INDUSTRY BREAKDOWN OF SAMPLE

S.I.C. Two-digit Industry Code	*Industry Title*	*Number of Firms*
29	Petroleum and coal products	11
49	Electric, gas and sanitary services	9
28	Chemicals and allied products	8
35	Machinery, except electrical	7
32	Stone, clay and glass products	5
33	Primary metal industries	5
37	Transportation equipment	4
20	Food and kindred products	3
26	Paper and allied products	3
10	Metal mining	2
36	Electrical equipment and supplies	2
59	Miscellaneous retail stores	2
	Other industries	8
		69

this study apply specifically to a sample of "survivor firms." As nonsurvivor firms lose their identity for a variety of reasons (e.g., corporate failure or merger with another firm), the difference in inferences drawn from a random sample of firms is not obvious. Table 1 details the industry composition (along S.I.C., two-digit industry codes) of the sample. Firms from twenty, two-digit industries are represented in the sample. Firms from four, two-digit industries comprise 43 percent of the sample—"petroleum and coal products" has the largest representation.[5]

The 1946–61 period (sixty-four observations) was used to estimate the Box-Jenkins model for each firm. The choice of sixty-four observations was based on several factors. First, a reasonably long hold-out period (1962–74) was desired to test the forecasting performance of the six models. Use of a short hold-out period would mean that forecasting tests would be subject to substantial sampling variation. Second, fifty to sixty observations is an upper limit to the data currently available on the Quarterly Compustat tape. Thus, our results will be of interest to other researchers who use the complete data set on Quarterly Compustat for model identification and estimation.

The 1946–61 period was used to identify and estimate the parameters of all the forecasting models. For forecasting observations in the 1962–74 period, an "adaptive forecasting" approach was adopted. That is, all data available at the time the forecast was made were used to forecast a future value of the series. The effect of continuously reestimating the parameters of the models also will be examined.

TIME-SERIES ANALYSIS

Cross-Sectional Autocorrelations

Table 2 presents the cross-sectional mean and standard deviation of the sample autocorrelations, up to a lag of 12. The mean and standard deviation are calculated from the autocorrelations of the sixty-nine firms over the 1946–74 period. The autocorrelations (r_j) are presented for four combinations of regular differencing (d) and seasonal differencing (D):

1. $d=0, D=0$
2. $d=1, D=0$
3. $d=0, D=1$
4. $d=1, D=1$.

Seasonal differencing involves four periods (quarters) per seasonal cycle. The estimated standard error for r_j up to a lag of 12 is approximately .09 for each combination of differencing.

If the time-series process implicit in

[5] The overlap between our sample and those in prior studies is not great. For instance, seventeen of the ninety-four firms in Brown and Kennelly [1972] and thirteen of the ninety-four firms in Griffin [1976] are included in our sample.

TABLE 2

CROSS-SECTIONAL SAMPLE AUTOCORRELATIONS: 1946–74 (MEAN AND STD. DEVIATION)

d	*D*	Lags *1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
		Panel A. Earnings Series											
0	0	.650	.521	.511	.618	.428	.349	.351	.452	.297	.238	.265	.377
		(.281)	(.347)	(.263)	(.210)	(.250)	(.305)	(.254)	(.248)	(.250)	(.287)	(.239)	(.224)
1	0	−.296	−.125	−.153	.408	−.162	−.076	−.139	.344	−.139	−.091	−.111	.304
		(.197)	(.310)	(.195)	(.281)	(.177)	(.284)	(.160)	(.258)	(.155)	(.257)	(.164)	(.251)
0	1	.445	.244	.128	−.121	.001	.019	−.017	−.034	−.026	−.032	−.008	−.005
		(.220)	(.205)	(.180)	(.233)	(.185)	(.179)	(.149)	(.145)	(.144)	(.143)	(.132)	(.133)
1	1	−.253	−.059	.106	−.335	.065	.052	−.014	−.019	.011	−.028	.020	.005
		(.172)	(.124)	(.154)	(.141)	(.140)	(.127)	(.115)	(.106)	(.090)	(.102)	(.097)	(.111)
		Panel B. Sales Series											
0	0	.890	.813	.772	.753	.682	.635	.614	.608	.554	.516	.505	.507
		(.075)	(.117)	(.086)	(.098)	(.104)	(.122)	(.108)	(.115)	(.111)	(.123)	(.107)	(.110)
1	0	−.171	−.063	−.112	.428	−.137	−.050	−.126	.346	−.108	−.069	−.115	.322
		(.248)	(.341)	(.195)	(.253)	(.164)	(.297)	(.142)	(.247)	(.150)	(.266)	(.140)	(.217)
0	1	.617	.418	.274	.065	.108	.111	.095	.071	.073	.067	.055	.052
		(.224)	(.200)	(.173)	(.223)	(.162)	(.149)	(.141)	(.155)	(.138)	(.136)	(.129)	(.121)
1	1	−.144	−.027	.090	−.351	.039	.027	.009	−.038	.027	.004	−.012	.024
		(.245)	(.118)	(.149)	(.153)	(.138)	(.124)	(.098)	(.132)	(.102)	(.078)	(.086)	(.108)
		Panel C. Expense Series											
0	0	.893	.821	.777	.753	.689	.645	.621	.613	.564	.529	.515	.512
		(.070)	(.101)	(.084)	(.099)	(.101)	(.113)	(.105)	(.109)	(.105)	(.111)	(.099)	(.103)
1	0	−.165	−.055	−.094	.396	−.115	−.050	−.112	.317	−.089	−.072	−.093	.289
		(.249)	(.329)	(.188)	(.248)	(.161)	(.288)	(.138)	(.236)	(.140)	(.258)	(.141)	(.216)
0	1	.605	.414	.266	.047	.102	.104	.087	.069	.072	.066	.059	.056
		(.234)	(.202)	(.176)	(.233)	(.161)	(.147)	(.139)	(.148)	(.135)	(.131)	(.124)	(.117)
1	1	−.155	−.018	.096	−.359	.050	.030	.034	−.036	.027	.001	−.009	.020
		(.252)	(.109)	(.144)	(.148)	(.143)	(.117)	(.102)	(.124)	(.108)	(.071)	(.079)	(.112)

Model 1 were an adequate description for each firm, the sample autocorrelations for the $d=0$, $D=1$ combination would be insignificantly different from zero—i.e., consistent with a $(p=0, d=0, q=0)\times(P=0, D=1, Q=0)_{s=4}$ model. If the time-series process implicit in Model 3 were an adequate description for each firm, the sample autocorrelations for the $d=1$, $D=0$ combination would be insignificantly different from zero—i.e., consistent with a $(p=0, d=1, q=0)\times(P=0, D=0, Q=0)_{S=4}$ model. Models 2 and 4 resemble Models 1 and 3, respectively, with the addition of a drift term.

Autocorrelations for the earnings series are presented in Panel A of Table 2. As expected, the levels of quarterly earnings are correlated highly over time—

$\bar{r}_1 = .650$ for the $d=0$, $D=0$ combination. The pattern of $\bar{r}_1$ to $\bar{r}_{12}$ suggests that differencing may be necessary for many firms in order to achieve a stationary series. Cross-sectionally, there is strong evidence of seasonality in quarterly earnings—$\bar{r}_4 = .408$, $\bar{r}_8 = .344$ and $\bar{r}_{12} = .304$ for the $d=1$, $D=0$ combination. That is, there is a strong correlation among quarterly earnings at time t, $t-4$, $t=8$, etc. This seasonality suggests that models 3 and 4 may be misspecified for many firms. Cross-sectionally, there is also evidence that successive fourth differences in quarterly earnings are autocorrelated —$\bar{r}_1 = .445$, $\bar{r}_2 = .244$ and $\bar{r}_3 = .128$ for the $d=0$, $D=1$ combination. That is, quarterly earnings in time t are not only related to quarterly earnings in time $t-4$, but also are related to the quarterly earnings reported between time $t-1$ and $t-5$. This evidence suggests that models 1 and 2 may be misspecified for many firms.

The autocorrelations for the sales and expense series are reported in Panels B and C, respectively, of Table 2. (The quarterly expense series is quarterly sales-quarterly earnings.) The patterns are quite similar to those observed for earnings. The main difference is that the serial correlation in both the levels of sales and expenses is higher than that in the levels ($d=0$, $D=0$ combination) of earnings. Note also that the values $\bar{r}_1$ to $\bar{r}_3$ ($d=0$, $D=1$ combination) for both sales and expenses are higher than the corresponding values for earnings.

The *cross-sectional* results are consistent with the quarterly earnings, sales and expense series each having both (1) an adjacent quarter-to-quarter component and (2) a seasonal component. The predictive ability of models incorporating these two components at the *individual firm* level is examined in a subsequent section.

Firm-Specific, Box-Jenkins-Identified Models

Appendix C of an earlier version of this paper [Foster, 1976] detailed the identified models for each of the earnings, sales and expense series of the sixty-nine firms. Several summary comments about the identified models are:

1. The most commonly identified processes for all three series involve either (a) M.A.(1)—seasonal M.A.(1) terms, or (b) A.R.(1)—seasonal M.A.(1) terms. Both these processes are consistent with quarterly series having an adjacent quarter-to-quarter component and a seasonal component. However, not all firms exhibit these two components.
2. Either first-differencing or seasonal-differencing is necessary to achieve stationarity for the sales series of all firms, the expense series of all but one firm and the earnings series of all but seven firms.
3. Seasonal terms appear in most identified models. The earnings series of sixty-four firms, the sales series of fifty-nine firms and the expense series of fifty-four firms included seasonal terms or seasonal differencing.

It is important to note that the above results across accounting series and across firms are not independent observations. The earnings series is a linear function of the sales and expense series, both of which are correlated cross-sectionally over time. Prior studies (e.g., Brown and Ball [1967]) also have documented cross-sectional commonalities in the earnings of firms. These dependencies mean that the significance tests presented in this paper should not be given undue weight. They are presented as guides in interpreting the results rather than as definitive tests of specific null hypotheses.

Predictive Ability Results: One-Step-Ahead Forecasting Performance

In this section, the ability of the six models to forecast the next observation in each series will be evaluated. This evaluation considers two factors. First, the accuracy of the forecasts will be examined. For every quarter/firm combination in the 1962–74 period, the forecast errors from the six models will be ranked in terms of accuracy. The model yielding the most accurate forecast for a particular quarter/firm will be given a rank of 1; the model yielding the least accurate forecast is given a rank of 6. Then, the average rank of each model over all firms and all quarters will be computed. A Friedman analysis-of-variance test will be used to examine the null hypothesis that the average rank of all six models is the same.[6] The alternative hypothesis is that the average rank of all six models is not the same. Results inconsistent with the null hypothesis may be induced by at least one model having a significantly different average rank.

The average rank test examines the *accuracy* of the forecasts produced via the six models. A second issue important in forecast evaluation is the relative *dispersion* of the forecast errors of each model. Two error metrics will be computed to examine the dispersion issue:

Mean Absolute Percentage Error

$$(\text{M.AB.E.}) = \left[\frac{Q_t - E(Q_t)}{Q_t}\right]$$

Mean Square Percentage Error (M.S.E.)

$$= \left[\frac{Q_t - E(Q_t)}{Q_t}\right]^2$$

where

Q_t = the actual quarterly variable in period t

$E(Q_t)$ = the expected quarterly variable for period t—this prediction is made at $t-1$ via a specific forecast model.

The M.AB.E. metric gives equal weighting to all forecast errors. (It assumes a linear loss function for forecast errors.) The M.S.E. metric gives greatest weight to large forecast errors. (It assumes a quadratic loss function for forecast errors.[7]) It is important to recognize that our measures of accuracy and dispersion are essentially surrogate criteria for evaluating alternative forecasting models. A more complete analysis would specify the loss function implicit in a specific decision context. Demski and Feltham [1972] provide an insightful discussion of this issue.

Table 3 contains the average rank, the M.AB.E. and M.S.E. for each of the six models. The results are presented for all four quarters combined, and separately for each of the four fiscal year quarters. The main features of the results in Table 3 are:

1. For all three series, there is a statis-

[6] Hollander and Wolfe [1973, pp. 138–146] provide a good description of this test. Significance levels for the S statistic used in the test are .05($\chi^2 = 11.07$), .01($\chi^2 = 15.08$) and .001($\chi^2 = 20.51$).

In addition to the problems of interpreting the results of this significance test that were noted previously, there is also the problem that several of the forecast models are "nested models." Note that the M.AB.E. and M.S.E. metrics are not affected by problems that "nested models" cause in ranking statistics.

[7] Both metrics encounter problems when the denominator is negative or very small. In cases in which the denominator is either negative or the computed percentage exceeds 100 percent, the M.AB.E. or M.S.E. was set at 100 percent. This procedure avoids the reported average dispersion measures being dominated by a few large observations. A similar approach was adopted in Brown and Niederhoffer [1968].

TABLE 3

SUMMARY STATISTICS FOR ONE-STEP-AHEAD FORECASTING: 1962–1974 PERIOD

Models	*All Four Quarters*			*First Quarter*			*Second Quarter*			*Third Quarter*			*Fourth Quarter*		
	Av. Rank.	*M.AB.E %*	*M.S.E. %*	*Av. Rank.*	*M.AB.E %*	*M.S.E. %*	*Av. Rank.*	*M.AB.E %*	*M.S.E. %*	*Av. Rank.*	*M.AB.E %*	*M.S.E. %*	*Av. Rank.*	*M.AB.E %*	*M.S.E. %*
							Panel A: Earnings Series								
Model 1	3.847	.287	.166	3.752	.304	.185	3.793	.256	.129	4.020	.296	.180	3.823	.292	.169
Model 2	3.395	.283	.167	3.317	.300	.185	3.366	.251	.130	3.478	.290	.180	3.420	.290	.173
Model 3	3.849	.346	.226	3.868	.396	.285	4.102	.335	.206	3.597	.308	.197	3.830	.343	.216
Model 4	3.598	.346	.227	3.699	.398	.287	3.667	.332	.204	3.473	.311	.200	3.551	.343	.217
Model 5	2.710	.258	.152	2.719	.287	.181	2.635	.218	.109	2.721	.264	.163	2.764	.262	.153
Model 6	3.598	.288	.171	3.643	.323	.215	3.433	.244	.121	3.709	.293	.177	3.608	.292	.169
Friedman ANOV-S Statistic	919.7			231.3			319.6			238.6			198.8		
							Panel B: Sales Series								
Model 1	4.464	.123	.028	4.343	.116	.024	4.386	.122	.027	4.612	.123	.028	4.515	.133	.032
Model 2	3.581	.110	.025	3.422	.102	.022	3.525	.109	.024	3.684	.110	.025	3.692	.121	.030
Model 3	3.667	.118	.033	3.736	.125	.033	3.985	.134	.043	3.381	.100	.028	3.567	.114	.029
Model 4	3.463	.118	.034	3.644	.125	.033	3.484	.132	.042	3.471	.102	.029	3.253	.113	.030
Model 5	2.812	.085	.018	2.832	.087	.018	2.653	.081	.017	2.848	.078	.015	2.916	.094	.022
Model 6	3.010	.088	.019	3.020	.092	.021	2.964	.086	.018	3.002	.018	.016	3.055	.094	.022
Friedman ANOV-S Statistic	1720.0			376.67			519.4			501.7			428.2		
							Panel C: Expense Series								
Model 1	4.496	.123	.029	4.331	.115	.024	4.463	.120	.027	4.667	.121	.026	4.522	.137	.037
Model 2	3.611	.110	.026	3.395	.100	.021	3.596	.107	.024	3.734	.107	.023	3.717	.125	.035
Model 3	3.616	.111	.029	3.724	.121	.032	3.904	.122	.034	3.307	.091	.022	3.528	.110	.027
Model 4	3.382	.110	.029	3.562	.121	.033	3.383	.119	.031	3.375	.092	.023	3.207	.109	.028
Model 5	2.853	.086	.020	2.881	.089	.020	2.692	.079	.017	2.888	.076	.014	2.950	.099	.028
Model 6	3.040	.088	.019	3.103	.094	.021	2.959	.084	.018	3.025	.077	.014	3.072	.095	.023
Friedman ANOV-S Statistic	1703.5			331.9			527.7			530.5			426.5		

tically significant difference in the average ranks of the six models.

2. For all three series, Model 5 has the lowest rank in each fiscal year quarter. Specifically, note that Model 5 always has a lower rank than Model 6 for each series—e.g., for all four quarters combined, the average rank of Model 5 is 2.710 for the earnings series while the corresponding average rank for Model 6 is 3.598. Note, however, that the difference between Models 5 and 6 is much less marked for both the sales and expense series than it is for the earnings series. For example, the average rank of the sales series for Models 5 and 6 are 2.812 and 3.010, respectively.
3. For the earnings series, the naive seasonal models (Models 1 and 2) have lower ranks than the nonseasonal naive models (Models 3 and 4)—e.g., the average rank for Model 2 (all 4 quarters) is 3.395 as opposed to an average rank of 3.598 for Model 4. For the sales and expense series, however, the ranks of the naive seasonal models are not consistently lower than those of the nonseasonal models. These results are consistent with the sample autocorrelation functions—the $\bar{r}_1$, $\bar{r}_2$, $\bar{r}_3$ of the $d=0$, $D=1$ combination for the sales and expense series exceed those for earnings series. That is, the adjacent quarter-to-quarter component of the sales and expense

time-series is much stronger than it is for the earnings time-series.

4. The average ranks and dispersion statistics suggest the general superiority of models incorporating a drift (δ) vis-a-vis corresponding models suppressing a drift—e.g., the average rank of Model 2 for sales (all four quarters) is 3.581 whereas the average rank for Model 1 (an equivalent model without a drift term) is 4.464. This result is not surprising given the common practice of firm's retaining earnings for re-investment. That is, over time an upward drift in earnings, sales and expenses is to be expected. Inflation may also induce an upward drift in each quarterly series.

Prior research found that a submartingale process describes well the process generating annual earnings for cross-sectional samples of U.S. firms (e.g., Ball and Watts [1972]). This process suggests the following expectation model for annual earnings:

$$E(AE_t) = AE_{t-1} + \delta \qquad (9)$$

where AE_t is annual earnings in period t and δ is an annual drift term. Such a process does not appear to provide an adequate *statistical* description of quarterly earnings, sales or expense series. The forecasting results in Table 3 indicate that a process which includes both (1) a seasonal component and (2) an adjacent quarter-to-quarter component has greater descriptive validity for each quarterly series. This conclusion has importance for the previously noted areas of accounting and finance in which time-series analysis is of interest. The conclusion also has importance for interim reporting issues, e.g., our results provide information on alternative models for forecasting sales. Such forecasts are used in several techniques for seasonally adjusting quarterly earnings.

Re-estimation of Model Parameters

The parameters in Models 2, 4, 5 and 6 were estimated from quarterly data over the 1946–61 period. Models 1 and 3, a seasonal random walk model and a random walk model, respectively, do not require parameter estimation. One limitation of these results in Table 3 is the possibility of structural change in the models over the 1946–74 period. As a check on this procedure, the parameters of Models 2, 4 and 5 were re-estimated prior to making each prediction over the 1962–74 period. (Model 6 was not re-estimated due to time and computer expense limitations.) The most recent sixty-four observations were used in the re-estimation of each model every quarter. Use of a different number of observations to re-estimate the models each quarter would mean that our results would compound the structural change issue with the issue of estimation efficiency.

Results for Model 5 are presented in Table 4 and are representative of those found for Models 2 and 4. The percentage reduction in mean square error (M.S.E.) when the parameters are re-estimated for the earnings series does not appear overly large (similarly, to a lesser extent, for the sales and expense series), e.g., the M.S.E. for the earnings series over the 1962–74 period is reduced from .1520 to .1514. It is difficult, however, to interpret what is a significant reduction in forecasting performance due to not re-estimating parameters of a forecasting model. One needs to examine the loss function in a specific decision context to address the "significance" issue. The analysis in the following section provides further evidence on this issue.

Several factors may explain the results

TABLE 4

EFFECT ON M.S.E. OF REESTIMATING PARAMETERS OF MODEL 5

Years	*Earnings Series*		*Sales Series*		*Expense Series*	
	Parameters Not Reestimated	*Parameters Reestimated*	*Parameters Not Reestimated*	*Parameters Reestimated*	*Parameters Not Reestimated*	*Parameters Reestimated*
1962–74	.1520	.1514	.0184	.0174	.0200	.0187
1962–63	.1529	.1528	.0135	.0137	.0162	.0158
1964–65	.0990	.0991	.0171	.0167	.0184	.0178
1966–67	.1224	.1215	.0151	.0136	.0182	.0159
1968–69	.1319	.1372	.0203	.0190	.0202	.0187
1970–71	.2414	.2395	.0253	.0245	.0285	.0282
1972–74	.1601	.1562	.0190	.0170	.0191	.0169

of Model 5 vis-a-vis Model 6 in Table 3. One is the problem of *identifying* Box-Jenkins models in finite samples. Some observed patterns in, say, the autocorrelation function may represent sampling variation rather than a component of the underlying time-series model. This sampling variation may lead to "overfitting" the sample data. This issue is explored further in Appendix A. A second factor is the problem of *estimating* Box-Jenkins models in finite samples. Model 5 usually involves fewer parameters than Model 6. Thus, Model 5 has more degrees of freedom in the estimation of its parameters. A third factor is *structural change*. Model 5 may be more robust to structural change in the post model-fit period than is Model 6. There is some evidence that this is the case. For instance, subperiod M.S.E. results for Models 5 and 6 for the earnings series (all four quarters combined) are:

Year	*Model 5*	*Model 6*
1962	.1699	.1564
1963	.1360	.1477
1964–65	.0990	.1324
1966–67	.1224	.1426
1968–69	.1319	.1507
1970–71	.2414	.2495
1972–74	.1601	.1897

Note, that in the year subsequent to the period Model 6 is identified and estimated, Model 6 actually has a lower M.S.E. than Model 5. An interesting extension of this paper would be to compare Model 5 vis-a-vis Model 6 when the parameters of both are re-estimated each quarter. One also could examine the effect of reidentifying Model 6 each quarter. We leave such extensions to further research.

PREDICTIVE ABILITY RESULTS: SECURITY RETURN ANALYSIS

Several of the forecast models used in this paper also have been used in prior studies on the security market reaction to accounting earnings, e.g., Models 1 and 2 were used by Brown and Kennelly [1972]. A natural extension of our analysis is to use all six models in examining the security market reaction to quarterly earnings. The role of forecast models in this context is in classifying firms into (1) those with positive unexpected earnings changes and (2) those with negative unexpected earnings changes. This analysis examines whether there is an association between unexpected earnings changes and relative risk-adjusted security returns. Given a maintained hypothesis of an efficient market, the strength of association is dependent on how accurately each expectation model captures the markets' expectation of one-step-ahead quarterly earnings.

Using the basic approach adopted in Ball and Brown [1968] and Brown and Kennelly [1972], we computed for each firm the cumulative average residual (CAR) for 60 trading days up to and including the earnings announcement date. The period of analysis included every quarter in the 1963–74 period. Earnings announcement dates were taken from *The Wall Street Journal Index*. The relative risk-adjusted daily security returns were taken from the *CRSP Daily Excess Returns Tape*. These returns were accumulated for each firm for each quarter for the -60-to-announcement-date period. Finally we computed the average cumulative average residual (CAR) for those firm/quarters in which the unexpected earnings change was (1) positive and (2) negative. A x^2 test for two samples was used to test for statistical significance.[8] We examine whether there is a statistically significant relationship between the sign of the unexpected earnings change and the sign of the cumulative average residual.

Table 5 contains the CAR results for all six models. As with Table 4, results are reported for all four quarters combined and separately for each fiscal year quarter. The CAR's for both (1) the positive earnings change firms and (2) the negative earnings change firms are reported separately in Table 5. The Composite CAR is the return from investing long in positive earnings change firms and selling short in negative earnings change firms. The main results in Table 5 are:

1. For models which incorporate seasonality in quarterly earnings (nos. 1, 2, 5 and 6), there is a significant association between the sign of the earnings change and the sign of the cumulative average residual—e.g., the composite CAR's for Models 2 and 5 (all quarters combined) are .0253 and .0222 respectively; the χ^2 values for Models 2 and 5 are 130.08 and 87.31, respectively. Thus, the significant association Brown and Kennelly [1972] report for the 1958–67 period also holds for the more recent 1963–74 period.
2. The nonseasonal forecasting models (nos. 3 and 4) show a much less significant association than the seasonal forecasting models—e.g., the composite CAR's for Models 3 and 4 (all quarters combined) are .0042 and .0042, respectively; the χ^2 values for Models 3 and 4 are .02 and .00, respectively. Both these χ^2 are not significantly different from zero. That is, a seasonally adjusted model better captures the market's expectation of next quarter's earnings than does a nonseasonal model.
3. Model 5 yields a higher CAR value and a higher χ^2 statistic than Model 6 in *every* fiscal quarter and for all four quarters combined; e.g., the CAR for Models 5 and 6 for the second quarter are .0251 ($\chi^2=44.51$) and .0162 ($\chi^2=20.98$), respectively. This result is consistent with the results in the fifth section.
4. For all four quarters combined, Model 2 has a higher CAR and χ^2 than Model 5. This is not a consistent result over all four quarters. Model 2 outperforms Model 5 in the first and third quarters; Model 5 outperforms Model 2 in the second and fourth quarters. This result is consistent with the difference between the one-step-ahead fore-

[8] See Siegel [1956, pp. 104–111] for a description of the Chi-square test. Significance levels for χ^2 with one degree of freedom are .05($\chi^2=3.82$), .01($\chi^2=15.09$) and .001($\chi^2=20.52$).

TABLE 5

QUARTERLY EARNINGS: CUMULATIVE AVERAGE RESIDUAL FOR PERIOD *FROM* 60 TRADING DAYS PRIOR TO ANNUAL ANNOUNCEMENT *TO* (AND INCLUDING) ANNOUNCEMENT DATE

	All Four Quarters			*First Quarter*			*Second Quarter*			*Third Quarter*			*Fourth Quarter*		
Models	$+ve$	$-ve$	*Composite*	$+ve$	$-ve$	*Composite*	$+ve$	$-ve$	*Composite*	$+ve$	$-ve$	*Composite*	$+ve$	$-ve$	*Composite*
Model 1	.0173	−.0325	.0217 (101.04)	.0221	−.0353	.0262 (21.76)	.0123	−.0393	.0202 (40.29)	.0276	−.0383	.0306 (44.65)	.0060	−.0183	.0098 (5.72)
Model 2	.0213	−.0326	.0253 (130.08)	.0267	−.0359	.0300 (33.03)	.0156	−.0359	.0229 (41.45)	.0312	−.0345	.0323 (42.48)	.0111	−.0243	.0158 (12.80)
Model 3	.0060	−.0021	.0042 (0.02)	−.0015	.0085	−.0055 (4.65)	.0008	−.0115	.0040 (0.00)	.0213	−.0000	−.0094 (2.43)	.0063	−.0127	.0090 (2.96)
Model 4	.0062	−.0020	.0042 (0.00)	−.0023	.0088	−.0061 (5.22)	.0005	−.0104	.0036 (0.04)	.0222	−.0003	.0098 (1.67)	.0070	−.0133	.0097 (3.61)
Model 5	.0202	−.0252	.0222 (87.31)	.0189	−.0159	.0177 (6.132)	.0178	−.0372	.0251 (44.51)	.0304	−.0261	.0288 (32.69)	.0133	−.0231	.0173 (14.56)
Model 6	.0143	−.0181	.0157 (38.39)	.0166	−.0110	.0141 (5.36)	.0097	−.0305	.0162 (20.98)	.0210	−.0115	.0176 (8.90)	-.0104	.0226	.0149 (7.33)

Notes (1) $+ve$ refers to group with positive earnings changes; $-ve$ refers to group with negative earnings changes; composite refers to policy of investing long in $+ve$ group and selling short in $-ve$ group.

(2) Number in parentheses in Composite column is the χ^2 statistic for a two-by-two contingency table for the association between the sign of the earnings change for each quarter and the sign of the C.A.R. for the −60-, to-, announcement-day period. Significance levels for χ^2 statistic are:

.05 $\chi^2 = 3.84$
.01 $\chi^2 = 6.64$
.001 $\chi^2 = 10.83$.

casting performance of Models 2 and 5 being of limited economic significance in the specific security market context examined. In other contexts, however, the difference between Models 2 and 5 could be important. Demski and Feltham [1972] stress that the economic importance of differences in the performance of forecasting models is context specific.

The parameters of the Models examined in Table 5 were all estimated using 1946–61 data. Results also were calculated with the parameters of Models 2, 4 and 5 being re-estimated every quarter. The re-estimation technique was described in the fifth section. Results were very similar to those reported in Table 5. Summary results for all four quarters combined were

Model 2: CAR $= .0257$ ($\chi^2 = 131.85$)
Model 4: CAR $= .0044$ ($\chi^2 = 0.00$)
Model 5: CAR $= .0219$ ($\chi^2 = 87.03$)

These results are consistent with those reported in the fifth section. That is, there is little evidence of major structural change affecting the predictive ability of the above earnings models in the two contexts in which predictive ability was examined.[9]

The sample autocorrelations reported in Panel A of Table 2 indicate significant cross-sectional seasonality in the quarterly earnings of the firms in this study. The finding that the capital market adjusts for this seasonality when interpreting each quarter's earnings change is quite interesting. One of the arguments industry has advanced against extensive interim disclosure is that investors would find the interim earnings of seasonal firms "misleading" or "confusing." Our results suggest that at the aggregate market level, this argument may not be descriptively valid. However, further analysis on this issue is required. For instance, one could examine whether the rankings of the seasonal and nonseasonal forecast models (based on the CAR) are different for highly seasonal firms than for nonseasonal firms.

The use of a daily security returns tape also allows examination of the speed with which the information in quarterly earnings is impounded into stock prices. Several authors have raised concerns about this issue. For instance, Anderson and Meyers [1975] state that given the use of monthly returns in prior CAR studies "it is not clear that there is any reliable evidence currently available concerning how soon accounting information is impounded in stock prices" [p. 23]. Table 6 contains the daily composite CAR for Model 2 (with parameters reestimated each quarter) for the 20 trading days before and after the announcement date. Note that day zero is the day earnings are announced in *The Wall Street Journal*. For many companies, this information is made available to the NYSE, etc., in the day prior to its publication in the *Journal*; i.e., the first edition of *The Wall Street Journal* on, say, January 26 reports information released to the market since the first edition of *The Wall Street Journal* of January 25. Table 6 also contains the χ^2 for the association between the sign of the earnings change for the quarter and the sign of the relative risk-adjusted security return on the relevant day. Note that it is only for the -1 and 0 trading days that the χ^2 is the highest of all the χ^2's examined; e.g., for all quarters combined, the χ^2 at -1 and 0 are 55.08 and 66.87, respectively, while the next highest χ^2 is 8.60 on the sixth trading day

[9] As noted before, the parameters of Model 6 were not reestimated every quarter. Apart from the indirect evidence in the fifth section, we make no inferences about the robustness of this model to any structural change in the post-model fit period.

TABLE 6

CUMULATIVE AVERAGE RESIDUAL FOR TRADING DAYS SURROUNDING QUARTERLY EARNINGS ANNOUNCEMENT

Trading Days Surrounding Announcement	All Four Quarters Composite CAR	χ^2	First Quarter Composite CAR	χ^2	Second Quarter Composite CAR	χ^2	Third Quarter Composite CAR	χ^2	Fourth Quarter Composite CAR	χ^2
−20	.0004	7.07	.0005	5.05	.0009	3.27	.0006	1.82	−.0002	0.00
−15	.0017	0.85	.0030	0.24	.0025	0.00	.0034	0.44	−.0022	2.96
−10	.0041	1.65	.0075	0.50	.0025	1.27	.0059	1.82	.0003	4.66
− 9	.0040	0.96	.0074	1.33	.0020	0.88	.0062	1.60	.0005	0.83
− 8	.0045	1.12	.0081	0.01	.0029	0.38	.0065	1.20	.0007	0.27
− 7	.0048	0.49	.0081	1.22	.0022	0.24	.0076	1.67	.0010	0.50
− 6	.0059	8.60	.0087	0.70	.0036	1.85	.0091	7.09	.0020	0.95
− 5	.0062	0.79	.0088	1.01	.0033	2.82	.0092	0.14	.0037	1.56
− 4	.0072	4.26	.0102	2.30	.0048	5.92	.0101	0.00	.0038	0.01
− 3	.0075	1.05	.0110	2.31	.0058	1.64	.0099	0.86	.0031	0.02
− 2	.0082	8.90	.0115	3.12	.0074	2.71	.0110	3.42	.0031	0.41
− 1	.0124	55.08	.0148	8.09	.0120	23.85	.0156	14.63	.0073	10.43
0	.0162	66.87	.0184	23.35	.0166	12.15	.0197	23.69	.0104	9.99
1	.0168	3.81	.0188	1.57	.0170	0.72	.0204	0.11	.0109	4.52
2	.0170	0.91	.0192	1.80	.0171	0.51	.0212	2.25	.0103	2.42
3	.0170	0.17	.0201	1.97	.0163	1.70	.0216	0.11	.0099	0.35
4	.0173	1.31	.0210	0.35	.0161	0.00	.0215	0.34	.0107	1.10
5	.0169	4.93	.0210	0.25	.0152	0.08	.0211	6.10	.0100	1.31
6	.0169	0.34	.0210	0.08	.0153	0.13	.0209	0.49	.0101	0.02
7	.0169	0.35	.0209	0.20	.0149	0.09	.0217	1.61	.0101	0.02
8	.0174	5.67	.0216	0.94	.0134	3.12	.0233	12.93	.0113	4.16
9	.0176	0.51	.0219	0.05	.0135	0.17	.0233	0.31	.0116	1.05
10	.0178	2.86	.0218	0.29	.0148	2.04	.0229	1.12	.0117	0.20
15	.0183	0.09	.0215	0.13	.0169	0.13	.0235	2.14	.0111	0.58
20	.0189	0.29	.0201	0.20	.0192	2.78	.0242	0.39	.0122	0.01

prior to the earnings announcement. That is, the market's reaction to the information contained in the quarterly earnings announcement appears to be concentrated in a 2-trading-day period.[10]

CONCLUSION

This paper has examined the time-series properties of the earning, sales and expense series of sixty-nine firms over the 1946–74 period. The predictive ability of six forecasting models for quarterly accounting data also was evaluated. Predictive ability was examined in two contexts: (1) the ability to forecast future values of the same series and (2) the ability to approximate the market's expectation of quarterly earnings when examining the security market reaction to accounting data. The main results of the analysis are:

1. Quarterly earnings, sales and expenses do not follow the submartingale process that appears to adequately describe annual earnings. Each quarterly series appears to have both (a) a seasonal component and (b) an adjacent quarter-to-quarter component. This conclusion is apparent from both inspection of the cross-sectional autocorrelation function and from the one-step-ahead forecasting results. A

[10] Brown and Hancock [1974] report similar results for the market reaction to the information contained in half-yearly earnings announcements by Australian companies.

forecasting model which took into account both the (a) and (b) components yielded more accurate one-step-ahead forecasts than models which incorporated only one of the components.

2. A parsimonious Box-Jenkins model with quarterly accounting data performed very well vis-a-vis Box-Jenkins models developed from a more detailed analysis of each firm's autocorrelation and partial autocorrelation functions. This result is consistent with that found by Watts [1970] with annual accounting data. Several reasons for this result were discussed in the paper.
3. Over the 1963–74 period, there is a strongly significant association between the sign of a firm's unexpected quarterly earnings' change and the sign of a firm's risk-adjusted security return in the 60 trading days up to and including the announcement date of each quarter's earnings.

Some specific results of interest-to-interim accounting issues include:

1. A Box-Jenkins A.R.(1) model provided more accurate (and less dispersed) forecasts of one-step-ahead sales than any of the other five models examined in this paper. Should the FASB require some seasonal adjustment of quarterly data (e.g., the allocation of fixed costs according to expected quarterly sales), this A.R.(1) model should be given serious consideration. At a minimum, it provides more accurate forecasts of one-step-ahead sales than some more naive models found in the accounting literature.
2. Cross-sectionally there is strong evidence of seasonality in the quarterly earnings of the sixty-nine firms examined. The security market analysis produced results consistent with the capital market adjusting for this seasonality when interpreting each quarter's earnings change. The capital market appears to be adjusting for seasonality by employing a forecast model that incorporates seasonal patterns in quarterly earnings. This result is inconsistent with many industry statements that quarterly earnings of seasonal firms are "misleading."

The analysis in this paper is univariate, i.e., we have examined *separately* each firm's earnings, sales and expense series. An important extension would be to analyze *jointly* the above series. The transfer-function approach outlined by Box and Jenkins [1970, Chs. 10–11] represents one approach to analyzing jointly the sales and expense series to produce predictions of the earnings series. The results in this paper should provide a useful benchmark for examining the improvements in predictive ability that joint-series analysis may offer over univariate analysis of time-series quarterly accounting data.

Appendix A

Model Identification in Finite Samples

The possibility of tentatively identifying diverse Box-Jenkins models across firms in finite samples, even when all firms have the same underlying time series, was discussed in the first section of this article. The one-step-ahead forecasting performance of Model 5, vis-a-vis Model 6, led us to examine this possibility in more detail. We assumed that an A.R.(1) in the seasonally differenced series was the underlying model for each firm. Then, ϕ_1 and δ were estimated from the sample, and the auto-

TABLE A.1
SAMPLE AUTOCORRELATIONS VS. SIMULATED AUTOCORRELATIONS FOR $(1, 0, 0) \times (0, 1, 0)_{s=4}$ MODEL

	Lags											
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
						A. *Earnings Series*						
Sample Estimates	.445 (.220)	.244 (.205)	.128 (.180)	−.121 (.233)	.001 (.185)	.019 (.179)	−.017 (.149)	−.034 (.145)	−.026 (.144)	−.032 (.143)	−.008 (.132)	−.005 (.133)
Simulated Estimates	.420 (.227)	.212 (.196)	.115 (.162)	.057 (.146)	.028 (.137)	.007 (.130)	−.002 (.123)	−.010 (.122)	−.015 (.122)	−.021 (.119)	−.023 (.113)	−.024 (.108)
						B. *Sales Series*						
Sample Estimates	.617 (.227)	.418 (.200)	.274 (.173)	.065 (.223)	.108 (.162)	.111 (.149)	.095 (.141)	.071 (.155)	.073 (.138)	.067 (.136)	.055 (.129)	.055 (.121)
Simulated Estimates	.581 (.226)	.383 (.223)	.257 (.215)	.179 (.196)	.127 (.182)	.090 (.174)	.060 (.166)	.035 (.159)	.021 (.151)	.007 (.143)	−.003 (.140)	−.013 (.133)
						C. *Expense Series*						
Sample Estimates	.605 (.234)	.414 (.202)	.266 (.176)	.047 (.233)	.102 (.161)	.104 (.147)	.087 (.139)	.069 (.148)	.072 (.135)	.066 (.131)	.059 (.124)	.056 (.117)
Simulated Estimates	.572 (.238)	.372 (.230)	.247 (.220)	.170 (.195)	.114 (.179)	.074 (.165)	.046 (.153)	.020 (.146)	.006 (.139)	−.003 (.132)	−.009 (.131)	−.014 (.133)

correlations that would be implied by this model were simulated. The residuals from each A.R.(1) were set to be distributed normally. Finally, the cross-sectional autocorrelations across all sixty-nine firms were computed. The $\bar{r}_j$'s and $\overline{\sigma(r_j\text{'s})}$ for all three series are reported in Table A.1. These $\bar{r}_j$'s and $\overline{\sigma(r_j\text{'s})}$ are the averages over ten simulations. The actual $\bar{r}_j$'s and $\overline{\sigma(r_j\text{'s})}$ for the three series are also presented in Table A.1 (these are from Table 2 for the $d=0$, $D=1$ series). With one exception, the simulated $\bar{r}_j$'s and $\overline{\sigma(r_j\text{'s})}$ from assuming a $(1, 0, 0) \times (0, 1, 0)_{s=4}$ model for all firms are quite close to the actual $\bar{r}_j$'s and $\overline{\sigma(r_j\text{'s})}$ observed in our sample. The one exception relates to $\bar{r}_4$ and $\overline{\sigma(r_4)}$. There is some evidence of a systematic pattern at lag 4 not captured by the $(1, 0, 0) \times (0, 1, 0)_{s=4}$ model. Note that the existence of this deviation from Model 5 does not necessarily mean one can (1) identify and estimate it at the individual firm level *and* (2) produce a model with better forecasting performance than a model which suppresses it. We leave this issue open for further research.

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