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Further Evidence on the Time-Series Properties of Annual Accounting Earnings

*Kyung-Joo Lee**

Contents

Ⅰ. Introduction

The time-series properties of accounting earnings have long been topics of considerable interest to researchers in accounting and finance. The primary focus of time-series research has been on the identification of a model or models that adequately describe the process generating corporate earnings. Accurate identification of a firm's earnings model is essential to the studies such as the firm valuation models, cost-of-capital estimates, predicting the failure of firms, and the relationship between accounting earnings and stock prices in that all of these studies require the forecasts of future earnings.

The studies on time-series behavior of accounting earnings have dealt either with

* 경상대학 회계학과 (Dept. of Accounting, Cheju Univ., Cheju-do, 690-756, Korea)

quarterly data or with annual data.[1] In this paper, I analyze only the annual earnings series to limit the scope of the study. The most common conclusion of the extant time-series research is that annual earnings are well represented by the random walk with a drift model.[2] For example, Ball and Watts (1972, p. 680) state : "Results from a variety of testing procedures lead us to the conclusion that measured accounting income is a submartingale or some very similar process." However, this conclusion was based on analyzing the means and medians of earnings series across firms (cross-sectional analysis).

Since mid-seventies, the Box and Jenkins (1976) (hereafter, BJ) methodology has been extensively applied to the time-series research in accounting earnings (See for example, Albrecht, Lookabill and McKeown (1977) and Watts and Leftwich (1977). The basic approach was to apply the BJ technique to each firm and to identify the best model describing the firm's annual earnings process (firm-specific BJ analysis).

Although the identified Box-Jenkins models were different across firms, they were not superior to a simple random walk model in forecasting future earnings. From this result, Watts and Leftwich (1977, p. 269) conclude : "The ability of random walk model to "outpredict" the identified Box Jenkins models suggests that the random walk is still a good description of process generating annual enrnings in general, and for individual firms." Despite this evidence on the superiority of the random walk model (hereafter, RW model) over the Box-Jenkins model (hereafter, BJ model), the results by Salamon and Smith (1977) and Brooks and Buckmaster (1976) suggest that there exists diversity across firms in the annual earnings models. Thus, it appears that the search for appropriate models of annual earnings is far from complete.

The purpose of this paper is to reexamine the time-series behavior of annual accounting earnings. The current study differs from previous work in several ways. First, this study uses an extensive number of firms (203) while the conclusion in previous studies is based on relatively small sample : 32 firms in Watts and Leftwich (1977) and 49 firms in Al-

1) As few as three parsimonious Box and Jenkins (1976) models have been suggested to describe fairly well the quarterly earnings process of most firms. The three models are a class of seasonal autoregressive integrated moving average (SARIMA) medels. In the notation of (pdq)x(PdQ), they are (100)x(010), (011)x(011) and (100)x(011). See Bao, Lewis, Lin and Manegold [1983] and Hopwood and McKeown [1986] for the literature review of time-series studies of quarterly earnings.

2) For excellent review of time-series research on annual earnings, see Lorek, Kee and Vass [1981] and Bao et al. [1983].

brecht et al. (1977). Second, the Akaike information criterion (described later) along with the BJ procedure is employed to identify the best earnings model for each firm. Finally, forecast errors from the BJ model are compared to those from the RW model with respect to their magnitudes as well as correlations with stock returns.

The results indicate that the annual earnings generating process is well described as a RW model. Specifically, I found 1) the RW model accounts for about half of sample firms (99 out off 203 firms); 2) autoregressive process is the most common BJ model for the remaining 104 firms; and 3) the BJ models are not superior to the RW model in forecasting and generating market expectation of future earnings.

The remainder of this paper is organized as follows. The next section describes the sample selection procedure, data and methodology. The identification of firm-specific BJ models, and the results of comparing the predictability and correlation for the BJ *vis-a-vis* RW model are discussed in Section 3. A summary of the results and concluding remarks appear in the final section.

II. Sample, Data and Methodology

The sample firms examined in this study were drawn from the Standard & Poor's Price-Dividends-Earnings (PDE) tapes and the University of Chicago Center for Research in Security Prices (CRSP) stock returns tape. To be included in sample, each firm must satisfy the following criteria: 1) annual earnings per share (EPS) data, adjusted for stock splits/dividends, was available in the PDE tapes over the 24 year period from 1962 to 1985; 2) complete stock returns data was availale on the CRSP tape since 1963; 3) fiscal year ending on December throughout the 24 year period; and 4) firms in the utilities and banking industry were excluded.

The first criterion was used to have earnings data enough for estimating time-series models by the BJ methodology. The second requirement was introduced to obtain data for the analysis of correlations between stock returns and earnings forecast errors. The third criterion was imposed to preserve comparability across firms. The fourth restriction was for ease of data collection. As is typical with time-series research, the familiar 'survivorship bias' applies to the sample because it includes only those firms that have existed for at least 24 years.

The above selection criteria yielded a sample of 203 firms. The sample firms represent 71 industries in 4-digit Standard Industrial Classification (SIC) code and 33 industries in 2-

digit SIC. The wide coverage of industries in the sample is useful for examining whether there exist systematic differnces across industries in the time-series properties of annual earnings.

While previous studies analyzed either net income or EPS, the EPS series was analyzed in this study for the following reasons. First, EPS is primary accounting number which has been suggested to affect the stock prices. Second, the findings in previous studies suggest that time-series properties of EPS and net income are quite similar.

The basic research methodology to be used in this paper is a two-step approach. In the first stage, the best model of EPS for each firm is identified from a class of the BJ autoregressive integrated moving average (ARIMA) models. The EPS data of 20 years (1962~1981) is used to estimate the models. The second stage involves the comparison of the BJ models with the RW model in terms of forecasting and correlation between stock returns and forecast errors using 4 years of EPS data (1982~1985). The maintained null hypothesis is that there is no difference between the BJ and RW models.

Ⅲ. Empirical Results

1. Cross-Sectional Analyses of Autocorrelations

Table 1 presents descriptive statistics of sample autocorrelation functions (SACF) across lags 1 through 5 for the 203 sample firms. The SACFs were estimated using EPS data over the 1962~1981 period. Note that the last 4 years of data, 1982~1985, were withheld for the predictability and correlation tests. The cross-sectional mean, standard deviation, and percentile of the SACFs are reportod for the original EPS series (Panel A) as well as for the first differencing (Panel B).

The raw EPS data exhibits strong positive autocorrelation with mean and median being 0.651 and 0.727 respectively, for lag 1. Since the estimated standard error for the SACF for lag 1 is approximately 0.224, the mean SACF is almost 3 times the standard error, indicating that the autocorrelations are significantly differnt from zero.[3] However, the EPS series exhibits increasing patterns, which are indicative of nonstationarity.

As is typical with economic data, the first differencing would make the EPS series

3) On the assumption that the series is completely random, the standard error of the SACF (r) for lag 1 is given by Bartlett's approximation as (Box and Jenkins [1976, p.35]) : var (r) = 1/N. Thus, SE(r) = $(1/20)^{1/2}$ = 0.224.

stationary. The mean (median) SACF of the differenced series is 0.053 (0.056). This suggests that changes in EPS are uncorrelated, which is consistent with the RW process. Nonetheless, top and bottom deciles of the SACF are significantly different from zero, implying that there may be firms whose EPS series are not characterized by the random walk model.

Table 1. Cross-sectional Distribution of Sample Autocorrelations[a]

Panel A. Original EPS Series

Lag	1	2	3	4	5
Mean	.651	.402	.232	.151	.113
Std Dev	.211	.279	.254	.187	.135
Percentiles					
.05	.196	-.161	-.270	-.210	-.192
.10	.341	-.037	-.135	-.110	-.094
.25	.501	.250	.045	.011	.053
.50	.727	.495	.309	.202	.142
.75	.813	.627	.435	.297	.204
.90	.853	.672	.505	.358	.253
.95	.868	.704	.536	.377	.283

Panel B. First Differences of EPS Series

Lag	1	2	3	4	5
Mean	.053	-.039	-.045	-.032	.041
Std Dev	.329	.269	.222	.191	.173
Percentiles					
.05	-.430	-.448	-.405	-.336	-.247
.10	-.365	-.369	-.312	-.276	-.195
.25	-.178	-.215	-.200	-.164	-.070
.50	.056	-.056	-.052	-.039	.038
.75	.290	.109	.106	.094	.156
.90	.487	.360	.264	.233	.279
.95	.688	.504	.342	.292	.331

[a] Cross-sectional statistics are based on 203 sample firms.

2. Estimation and Identification of Firm-Specific BJ Models

While the cross-sectional patterns exhibited by SACFs in Table 1 provide some supports for the RW model as annual earnings process, the same mean/median results also can be obtained even if different firms have different earnings models. For example, the EPS series of some firms may have significant negative serial correlations in EPS changes (first differencing) which may be offset by positive correlations in other firms' EPS, and *vice versa*. In this section, I describe the procedures for identifying the best firm-specific BJ models and provide the identification results.

The general form of the ARIMA model can be stated as :

$$(1-B^{k})X_t = \mu + \frac{\theta(B)}{\phi(B)} a_t \cdots\cdots\cdots\cdots (1)$$

where X_t represents the EPS at year t, $\theta(B)$ is the moving average (MA) model, $\phi(B)$ is the autoregressive (AR) model, μ is the constant term, a_t is an independent and identically distributed random variable ('white noise') with zero mean and constant variance, and B is a backward shift operator such that $B^k X_t = X_{t-k}$.

The essence of the BJ methodolgy for selecting a model is the iterative procedure of identification, estimation and diagnostic checking. This procedure requires a researcher to make judgement in identifying a preliminary model from the sample characteristics (such as SACF) of the series and interpreting the results of diagnostic tests.

While it is feasible to apply the BJ iterative procedure extensively to small number of series, this procedure is unlikely to be applicable when large number of series are analyzed as in this study because of huge cost (in time and effort) involved in carrying out the procedure. Fortunately, there exist noniterative procedures that also lead to the selection of a unique model. Two of such procedures are the Akaike method and the Predictability method. In this study, I utilize the Akaike procedure in identifying models of the firm's EPS. [4]

The basic notion of the crterion introduced by Akaike (1974) for selecting a model is that among a large set of models, the one which maximizes the use of information in data is the model that fits the data best. Akaike shows that the best model is the one that minimizes the following information index, usually referred to as the Akaike Information Criterion (AIC) :

$$AIC = -2\ell n(L) + 2K$$

4) The choice of the Akaike procedure over the Predictability procedure was based on i) empirical evidence suggesting that the models identified by both procedures are similar (Dharan [1983]), and ii) small number of observations (maxmimum of only 20 years). Note that the Predictability procedure requries separate observations for model identification and predictability test.

where L is the likelihood function and K is the number of parameters.[5]

The Akaike procedure requires a set of predetermined models from which a model can be selected by minimizing the AIC. I considered 18 parsimonious ARIMA(pdq) models that have $p \leq 2$, $q \leq 2$ and $d \leq 1$. Thus, the most complex model considered was ARIMA(212). More complex models were excluded due to the potential difficulty in estimating significant parameters with relatively small observations (maximum of 20 years).

The 'best-fitting' earnings model for a firm was identified in the following manner. First, each of 18 ARIMA models was estimated using maximum-likelihood method. Maximum number of 40 iterations was used in the estimation process. Second, the 'lack of fitness' test was conducted for each estimated model using the following statistic by Ljung and Box (1978) :

$$X^2 = n(n+2)\sum_{k=1}^{m} r_k/(n-k)$$

where $r_k = \sum_{k=1}^{n-k} a_t \cdot a_{t+k} / \sum_{k=1}^{n} a_k$, n is the number of residuals, m is the number of lags, and a_t is the 'white noise' process. This statistic is approximately chi-square distributed with m degrees of freedom (12 in this study). If the X^2 value of a model is large enough to give the probability of type-I error greater than 10%, the model was eliminated.[6] Finally, the remaining models were ranked by the AIC. The model with the lowest AIC was selected as the 'best-fitting' earnings model for the firm, subject to the significance of the estimated parameters. The above procedure was applied to each of 203 firms. Thus, total of 3,654 models (203x18) were estimated, and their X^2 values and AICs were examined.

Table 2 presents frequency distribution of the 'best-ftting' earnings models. The most commonly identified model is the RW model, ARIMA(010), which accounts for 99 firms (48.7%).[7] Several points are worth noting from Table 2. First, all of the identified models

5) It is well known in the literature that the AIC will tend to identify a model with too many parameters compared to the true meodel even in large samples. A Baysian criterion has been proposed by Schwartz [1978] which mitigates this problem. I applied Schwatz's Baysian Criterion (SBC) as well as AIC to the identification of earnings models. There were only 25 cases for which both criteria selected different models.

6) There were only 4 EPS series that failed the chi-square criterion for all of 18 estimated models. For these firms, the earnings models were selected based solely on the AIC.

7) Out of 99 random walk models identified, the estimates of constant term were significantly different from zero for 36 cases (RW with a drift model) while 66 firms had constant term not different from zero.

have first differencing. This indicates that annul EPS exhibits nonstationarity and the time-series analysis on annual earnings should use differencing in the first place. Second,

Table 2. Frequency Distribution of the 'Best-Fitting' Time-Series Models[a]

Model (pdq)	Frequency	Percent
010	99[b]	48.7
110	42	20.7
210	32	15.8
011	23	11.3
012	5	2.5
111	1	0.5
112	1	0.0
Total	203	100.0

[a] Each of 203 identified models were estimated using 20 years of EPS data (1962-1981). The criteria for selecting the best model wer i) AIC, ii) BPQ statistic, and iii) significance of parameter estimates.

[b] Out of 99 random walk model identified, the estimates of constant term were significantly different from zero for 36 cases (random walk with drift model) while 66 firms had constant term not different from zero.

Table 3. Frequency Distribution of the 'Best-Fitting' Time-Series Models by Industry[a]

Industry (SIC)	Model (pdq)							Total
	010	110	210	011	012	111	112	
10	2		5	2				9
20	3	3		2		1		9
26	3	4	2					9
28	11	11	6	1	1			30
29	8			4	1			5
32	5		3	1				9
33	11	3	1					15
34		1	1	1	1		1	5
35	7	6	1	1				15
36	12	4	3	4	1			23
37	11	1	1	2	1			16
38	7	2	1					10
45	4	1						5
Total	84	36	24	18	4	1	1	168

[a] Only those industries (2-digit SIC) that have five or more firms are included in the analysis.

other than the RW model, annual earnings appear to be well described by an AR process. AR models account for 74 firms (36.5%). Finally, the results reveal that annual EPS can be represented by a class of simple ARIMA models. There are only 2 firms that have both AR and MA parameters.

Table 3 shows frequency distribution of the identified models by industry (2-digit SIC). The use of 2-digit SIC is most successful at grouping similar firms (Clarke (1989)). To make the analysis meaningful, only those industries with 5 or more firms were included in the analysis, resulting in 168 firms. The RW model was dominant in most of the industries. Petroleum (SIC 29), Primary Metal (SIC 33), Transportation Equipment (SIC 37), Instruments (SIS 38), and Airlines (SIC 45) industries had the RW model which accounts for more than 60% of their member firms. Noticeable exception was Fabricated Metal (SIC 34) industry which had no firms whose earnings are described by the RW model.

3. Predictability Tests

The results in the preceding section suggest that almost half (99) of the 203 sample firms have the RW model as their earnings generating process. In this section, I analyze the remaining 104 firms for the relative performance of their BJ models in forecasting future earnings compared to the RW model. More specifically, forecast errors from the BJ models were compared with those from the RW model. One-year-ahead as well as two-year-ahead forecasts were examined.

The forecast error is the difference between actual EPS and forecasted one. For one-year-ahead forecasts, predictions of EPS were made for 1982, 1983 and 1984 by reestimating the models each year from the data prior to the prediction year. For example, the forecasts for 1983 were based on the estimated models (BJ and RW) using EPS data from 1962 to 1982. For two-year-ahead forecasts, earnings predictions were made for 1983, 1984 and 1985.

Two forecast error metrics were used. The first metric is the absolute percentage error (APE) defined as :

$$APE_{it} = \left| \frac{X_{it} - F_{it}}{X_{it}} \right|$$

where

X_{it} = actual earnings per share (EPS) for firm i in year t.

F_{it} = forecasted EPS for firm i in year t.

The second forecast error metric is the squared percentage error (SPE) :

$$SPE_{it} = \left[\frac{X_{it}-F_{it}}{X_{it}}\right]^2$$

APE is consistent with a linear loss function while SPE is consistent with a quadratic loss function.

To examine whether significant difference exists between the BJ and RW models in forecasting future earnings, the forecast error metrics from two models were matched pairwise and the significance of the mean difference was tested. The usual parametric test

Table 4. Mean Forecast Errors of One-Year-Ahead Predictions : Box-Jenkins (BJ) Model vs Random Walk (RW) Model [a)]

Panel A. Mean Absolute Percentage Error (MAPE)

	Year			All years
	1982	1983	1984	
BJ	.94	.70	.66	.77
RW	.90	.64	.56	.70
t-stat [b)]	.84	1.29	2.21	2.77
Prob>|t| [c)]	.40	.20	.03	.01
Z-stat [d)]	.27	1.42	.84	.56
prob>|Z|	.79	.16	.40	.58

Panel B. Mean Squared Error (MSE)

	Year			All years
	1982	1983	1984	
BJ	1.03	.63	.65	.77
RW	.92	.59	.53	.68
t-stat	1.98	.60	2.01	2.86
Prob>|t|	.05	.55	.05	.01
Z-stat	.41	1.40	.83	.55
Prob>|Z|	.68	.16	.41	.58

[a] Using 104 firms whose EPS series are described by a class of ARIMA models other than random walk model (010). all forecast errors greater than 300% were truncated to 300%.

[b] Test statistic from the matched paired t-test.

[c] Probability for two-tailed test.

[d] Test statistic from the Wilcoxon Signed Ranks test.

for mean difference is the paired t-test. Since the error measures were stated in percentage form, they are likely to suffer from extreme values (outliers) problem which in turn would lead to the violation of distributional assumptions of the paired t-test. Therefore, forecast errors greater than 300% were truncated to 300% prior to conducting the test. A nonparametric alternative to the paired t-test is the Wilcoxon Signed Ranks test. This test is insensitive to the outliers. Both tests were used.

Table 4 presents the results of compaaring the mean forecast errors of one-year-ahead predictions from the BJ model *vis-a-vis* the RW model. The results are reported for two error metrics and for each year as well as overall years. Surprisingly, forecasts from the RW model were more accurate than those from the BJ models each year regardless of the

Table 5. Mean Forecast Errors of Two-Year-Ahead Predictions : Box-Jenkins (BJ) Model vs Random Walk (RW) Model[a]

Panel A. Mean absolute Percentage Error (MAPE)

	Year			All years
	1983	1984	1985	
BJ	.91	.88	.92	.91
RW	.81	.76	.87	.82
t-stat[b]	1.52	2.23	1.46	2.77
Prob>|t|[c]	.13	.03	.15	.01
Z-stat[d]	.78	.92	.14	.53
Prob>|Z|	.43	.36	.89	.60

Panel B. Mean Squared Error (MSE)

	Year			All years
	1983	1984	1985	
BJ	.95	.84	.94	.91
RW	.83	.74	.87	.82
t-stat	1.55	1.49	1.28	2.39
Prob>|Z|	.12	.14	.20	.02
Z-stat	.78	.90	.17	.50
Prob>|Z|	.44	.37	.87	.62

[a] Using 104 firms whose EPS series are described by a class of ARIMA models other than random walk model (010). All forecast errors greater than 300% were truncated to 300%.

[b] Test statistic from the matched paired t-test.

[c] Probability for two-tailed test.

[d] Test statistic from the Wilcoxon Signed Ranks test.

error metrics used. The differences were statistically significant ($\alpha < 0.01$) for overall years when the paired t-test was used while the Wilcoxon test indicated that the differences were insignificant.

The results of comparing two-year-ahead forecasts are reported in Table 5. As with one-year-ahead forecasts, the RW model generated more accurate predictions than the firm-

Table 6. Earnings Per Share (EPS) by Year

Year	Random Walk Firms (N=99)				Non-RW Firms (N=104)			
	Mean ($)	Std Dev	Med ($)	Mean Index	Mean ($)	Std Dev	Med ($)	Mean Index
1962	.822	.815	.565	1.000	.731	.651	.599	1.000
1963	.941	.930	.627	1.145	.808	.732	.680	1.105
1964	1.097	1.012	.808	1.335	.975	.859	.812	1.334
1965	1.260	1.243	.973	1.533	1.078	.936	.915	1.475
1966	1.356	1.514	1.110	1.650	1.221	.916	1.044	1.670
1967	1.198	1.261	.952	1.457	1.157	.919	.984	1.583
1968	1.278	1.218	1.073	1.555	1.248	1.020	1.008	1.707
1969	1.303	1.110	1.101	1.585	1.230	.986	.997	1.683
1970	.899	1.691	.836	1.094	1.070	1.032	.916	1.464
1971	1.024	1.237	.850	1.246	1.078	.980	.953	1.475
1972	1.369	1.393	1.173	1.665	1.306	1.142	1.145	1.787
1973	1.926	1.448	1.410	2.343	1.804	1.451	1.430	2.468
1974	2.313	2.590	1.680	2.814	2.017	1.664	1.530	2.759
1975	1.739	1.416	1.540	2.116	1.714	1.614	1.522	2.345
1976	2.288	1.584	2.069	2.783	2.108	1.574	1.959	2.884
1977	2.397	2.191	2.364	2.916	1.841	2.047	1.847	2.518
1978	2.940	2.153	2.739	3.577	2.324	1.783	2.170	3.179
1979	3.596	2.751	3.309	4.375	3.109	3.352	2.918	4.253
1980	3.297	2.801	3.288	4.011	2.851	3.771	2.719	3.900
1981	3.253	2.914	3.090	3.957	3.029	2.750	2.707	4.144
1982	.898	4.675	1.439	1.092	1.168	5.154	2.129	1.598
1983	1.295	3.998	2.029	1.575	2.177	2.876	2.433	2.978
1984	2.726	3.717	2.919	3.316	2.787	3.393	2.994	3.813
1985	.515	7.779	2.039	.627	2.166	4.482	2.189	2.963

specific BJ models. Once again, the differences were significant at α less than 2% level when the t-test was used while they were insignificant using the Wilcoxon test.

Two possible explanations come to mind for the findings that the RW model is as good as the BJ models in forecasting earnings. First, the identified BJ models may be misspecified due to small number of observations. Given the suggestion by BJ (1976, p. 18) that at least 50 observations should be used to estimated a model, use of only 20 observations might result in the misspecification of the model. Unfortunately, this possibility could not be examined. Second, there might be structural shifts in the EPS series from the estimation period to forecasting period. In an attempt to investigate this possibility, the patterns of earnings series were examined.

Table 6 provides summary statistics of EPS series each yeaar over the period from 1962 to 1985. Mean, median, standard deviation, and mean index (mean EPS relative to mean EPS in 1962) of earnings were presented for the RW model firms (99) and the non-RW firms (104). The results reveal that EPS series was increasing until 1981 and then large decrease occurred in 1982. In other words, there was a structural change in EPS series in 1982. Recall that the models were estimated and identified using data up to 1981, while forecasts were made since 1982. The results in Table 6 suggest that relatively superior performance of the RW model over the BJ models was in part due to the structural shifts in earnings series.

4. Correlation Tests

One of the most important applications of the earnings models to accounting research is the study which examines the relation between accounting earnings and stock returns, usually referred to as 'information content of earnings' studies. The essential issue here is whether investors use earnings data in making their investment decisions. If investors indeed use earnings data, the stock prices will react to, *ceteris paribus*, the firms' releases of earnings numbers.

As rational individuals, investors are assumed to make predictions about the firms' unrealized earnings. Hence, changes in stock prices will occur only if the realized earnings are different from the investors' (or market's) expectations. Since investors' expectations of earnings are unobservable, researchers have used the forecasts from the time-series models as proxies for the market's expectations.

In this paradigm of research, the earnings model which generates the forecast errors most highly correlated with stock price changes is considered to be the best model utilized by the market. Thus, the criterion for evaluating time-series models is the magnitude of correlation between stock returns and earnings forecast errors. In this section, I compare the BJ models with the RW models for 104 firms by employing the correlation test. The basic research design is to estimate the correlations between 'unexpected' stock returns over a year and 'unexpected' earnings, and to compare the magnitudes of correlations between the BJ and RW models.

Unexpected stock returns (hereafter, abnormal returns) are defined as the difference between actual returns and expected returns during, say, a month. Typically, expected returns are obtained by estimating the following regression model, usually referred to as the 'market model' :

$$R_{i\tau} = \alpha_i + \beta_i R_{m\tau} + \varepsilon_{it}$$

where : $R_{i\tau}$ = stock returns for firm i during month τ,

$R_{m\tau}$ = returns of the market portfolio during month τ,

α_i, β_i = intercept nad slope coefficients for firm i.

The above market model was estimated by ordinary least square (OLS) regression using time-series data of 60 monthly returns up to the beginning of the firm's fiscal year for which correlation tests were conducted (1982, 1983, and 1984). The abnormal returns were calculated each month during the year and cumulated over a specific period to get cumulative abnormal returns (CAR) :

$$CAR_{it}\ [T1 : T2] = \sum_{\tau=T1}^{T2} R_{i\tau} - (\hat{\alpha}_i + \hat{\beta}_i R_{m\tau})$$

Two measures of CAR were used depending on the cumulation period. Cumulation period was 12 months either from January to December (CAR[1 : 12]) or from April to March of the following year (CAR[4 : 15]).[8]

Unexpected earnings (UE) are differences between actual EPS and forecasted one. Following the convention in accounting research, two UE metrics were used : a) price-deflated UE which uses as deflator the stock price at the beginng of the year; and b)

8) The reason for using CAR[4 : 15] is that actual annual earnings are not released until March of the following year for some firms. For most of the firms, annual earnings are available in the market during February of the following year. The study which used CAR [4 : 15] is Beaver, Clark and Wright [1979].

percentage UE which is deflated by the forecasted EPS. To avoid extreme values problem, observations with |UE|>300% were excluded from the analysis.

By denoting corr(CAR, UE) as the correlation coefficient between CAR and UE, the null and alternative hypothesis in this study can be stated as follows :

$$H_0 : \text{corr}(CAR, UE)_{BJ} = \text{corr}(CAR, UE)_{RW}$$
$$H_a : \text{corr}(CAR, UE)_{BJ} \neq \text{corr}(CAR, UE)_{RW}$$

This hypothesis was tested using the following test statistic which has a standard normal distribution (See Morrison [1976, pp. 104~105]) :

$$Z = \frac{Z_{BJ}-Z_{RW}}{[(1/(N_{BJ}-3)+1/(N_{RW}-3)]^{+}}$$

where Z is a normally distributed variate from the Fisher's transformation of sample correlation (r) : $Z = 1/2\ell n(1+r/1-r)$, and N is the number of observations.

Table 7 provedes evidence on the differences in correlation coefficients between CAR for the BJ models *vis-a-vis* the RW model. Two measures of correlations, Pearson Product Moment and Spearman Rank correlations, were used. Consistent with the Pearson Product (e.g., Beaver, Clarke and Wright [1979]), the correlations were positive and statistically significant. Furthermore, the results indicate thaat the correlations are stronger for UE measures from the RW models than from the BJ models. However, the differeces were

Table 7. Correlations Between Unexpected Earnings and Abnormal Stock Returns (CAR) : Box-Jenkins (BJ) vs Random Walk (RW) Model

Panel A. Price-Deflated Unexpected Earnings

Corr	CAR[1 : 12]			CAR[4 : 15]		
	BJ	RW	Z-stat	BJ	RW	Z-stat
Pearson	.330	.425	-1.385	.185	.267	-1.083
Spearman	.293	.311	-.250	.171	.179	-0.99

Panle B. Percentage Unexpected Earnings

Corr	CAR[1 : 12]			CAR[4 : 15]		
	BJ	RW	Z-stat	BJ	RW	Z-stat
Pearson	.292	.323	-.425	.204	.245	-.539
Spearman	.288	.294	-.087	.155	.168	-.170

not large enough to reject the null hypothesis. These results were robust with respect to different measures of UE, CAR, or correlation.

Ⅳ. Conclusion

This study attempts to identify the time-series model which best describes annual accounting earings using a sample of 203 firms. Differently from the previous studies, the analysis in this paper utilized the Akaike information criterion to select the best earnings model for each of the sample firms. I also compared the BJ models with the RW models in terms of their ability to forecast future earnings (predictability tests) and to generate forecasts which proxy for the market's expectations of earnings (correlation tests). The main results of the analyses are :

1) Annual EPS series can be well represented by the RW model for large portion of sample firms. About half (99) of the sample firms were identified as the RW model from the initial model selection procedure.

2) AR process was the most common BJ model for the remaining 104 non-RW model firms, which accounts for 74 firms.

3) All of the identified models had first differencing, suggesting that annual EPS series exhibits nonstationarity.

4) There exist no systematic differences in the time-series models across industries. The RW model was the dominant one in almost all of the industries.

5) The RW model was as good as the firm-specific BJ models in forecastiong future earnings. This result was robust with respect to both one-year-ahead and two-year-ahead forecasts.

6) While not statistically significant, the forecasts from the RW model were more closely related to the stock price changes than those from the BJ model.

Overall, these results lead to the conclusion that annual accounting earnings generating process can be adequately characterized as a random walk model. Indeed, the results in this study corroborate the findings in the previous studies.

The limitations of the analyses reported in this paper should be emphasized in interpreting the results. First, the sample used in this study suffers from the 'survivorship bias'. The sample selection procedures eliminated non-December fiscal year ending firms, bankrupted firms, and recently organized firms. Thus, this study's conclusion is applicable only to large and established firms. Second, the results were solely based on univariate analysis. Since corporate earnings are usually affected by general economic conditions, a multivariate analysis which incorporates market indx such as GNP should be conducted before making a definite conclusion regarding the time-series prorerties of annual accounting earnings.

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〈국문초록〉

연간회계이익의 시계열속성에 관한 재검토

이 경 주

본 연구의 목적은 연간회계이익(annual earnings)의 시계열속성을 재검토하는 것이다. 기존 연구결과에 의하면 랜덤웍(random walk : 이하 RW) 모형이 Box와 Jenkins 기법을 적용하여 도출한 모형(이하 BJ모형)에 비하여 예측능력에 있어서 우수하다고 결론짓고 있다. 그러나 연간회계이익의 창출과정(earnings generating process)에 대한 설명능력을 기준으로 평가하는 경우에는 BJ모형이 RW모형보다 우수한 것으로 나타나고 있어, 두 모형간의 상대적 우위에 관해서는 아직까지 명확한 결론이 내려지고 있지 않다. 따라서 본 연구에서는 과거의 연구와는 달리 (1) 분석대상 표본기업의 수를 늘리고, (2) BJ기법과 함께 Akaike 정보기준(Aiaike information criterion : AIC)을 적용하여 최적 시계열모형을 추정 · 선택하며, (3) RW모형과 BJ모형의 비교기준으로 예측오차 뿐만아니라 예측오차와 초과수익율의 상관관계를 분석함으로써 연간회계이익의 시계열속성을 가장 대표할 수 있는 최적모형을 탐색하였다.

미국 상장기업 203개를 표본으로하고 24년(1962~1985) 동안의 주당순이익 자료를 이용한 실증분석결과는 다음과 같이 요약된다. 첫째, 표본기업의 절반정도(94)는 RW모형이 연간회계이익을 가장 잘 설명하는 것으로 나타났다. 둘째, BJ모형으로 대표되는 기업군(104)에 대하여 가장 공통적인 시계열모형은 자기회귀(autoregressive : AR) 모형이었다. 셋째, 업종간에 연간회계이익의 시계열속성은 통계적으로 유의한 차이를 보이지 않는다. 네째, 전반적으로 RW모형이 BJ모형에 비하여 1년 후와 2년 후의 회계이익을 예측함에 있어서 보다 정확하였다. 다섯째, 통계적으로 유의하지는 않았으나 RW모형에 의한 예측오차가 BJ모형에 의한 예측오차에 비하여 초과수익율과 보다 높은 상관관계를 갖는다. 이와같은 결과는 연간회계이익의 시계열속성이 RW모형에 의하여 가장 잘 설명되어짐을 보여주는 것이다.