Faculty Working Papers

AN EMPIRICAL SURVEY OF TRANSFER-FUNCTION AND UNIVARIATE TIME-SERIES EARNINGS EXPECTATION MODELS

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#649

College of Commerce and Business Administration
University of Illinois at Urbana-Champaign

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rankings given the linear and logarithmic specification

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Summary:

This study investigated univariate and multivariate statistical models in the context of their relative ability to serve as a market earnings expectation model (EEM). Included were univariate time series models, bivariate regression models and two bivariate multiple time series (transfer function) models developed by the authors. The models were compared on: (1) how well they fit the data, (2) their ability to perform in a capital market context and, (3) forecast accuracy.

The results indicated on all three comparisons that a multivariate model is the more appropriate specification. In particular, it was found that the model of Ball and Brown and the authors' transfer function model (authors' model 1) outperformed all other models considered, including the univariate time series typically found in the literature.

A growing body of literature has dealt with the forecasting of quarterly earnings. This research has grown along two lines (see Foster [1977] for a detailed discussion): 1) Forecast methods have been compared based on their relative ability to forecast future earnings, 2) They have been compared based on their relative ability to approximate the capital markets' expectation when measuring market reaction to accounting data.

This paper lies primarily in category two and secondarily in category one. Specifically, the purpose of the present research is to bring together the various statistical forecast models used in the literature and assess their relative ability to approximate the markets' expectation for earnings in the context of the capital market. These models are assessed based upon 1) how well they are specified based upon diagnostic statistics, 2) their relative ability to approximate the market expectation model and, 3) forecast accuracy. In addition, this study introduces a new multivariate expectation model [transfer function] for earnings and investigates the ability of this model to perform relative to univariate time-series models.

A major reason for considering how well a given model approximates the market expectation for earnings is that research in the accounting informational/capital market literature (e.g., Brown and Kennelly [1972] relies upon the choice of an earnings expectation model. For example, Foster [1977, p. 2] wrote: "choice of an inappropriate model (one inconsistent with the time series) may lead to erroneous inferences about the information content of accounting data." Also the use of an earnings expectation model has been important to studies relating to the estimation of the cost of capital, dividend policy and the association of alternative earnings measures.

A motivation for the present study is that in most of the previous research, the particular choice of an earnings expectation model (henceforth EEM) was made in an ad hoc fashion without regard to the applicability of alternative EEM's. Foster [1977] recognized this problem and compared a proposed model to several previously considered models and his results indicated that the capital markets' EEM includes both quarter-to-quarter and seasonal components. Subsequent research [Collins and Hopwood, 1980] found that the models of Griffin [1977], Watts [1975], and Brown and Rozeff [1979] produce forecasts more accurate than those of the model considered by Foster. These studies, however, focused on accuracy and not on the ability of a model to approximate the markets' EEM. In addition, none of these studies, including Foster's, considered the relative ability of univariate versus multivariate models to approximate the market EEM. Therefore, in the present study, both univariate and multivariate models will be examined for their ability to approximate the market EEM.

The paper is presented in four major parts. In the first part, previous models are discussed and diagnostic statistics relating to their appropriateness are presented. This is followed by the introduction of a multivariate transfer model and diagnostic statistics associated with its specification. The second part contains empirical results with respect to the capital market, and part three focuses on the models' relative forecast accuracy. Part four presents a summary and conclusion.

1.0 Models Previously Used in the Literature

1.10 Background

Earnings expectation models can be classified as univariate and multivariate. We use the term multivariate to include models which consider the structural relationship between two or more variables. These include the model of Ball and Brown [1968] who regressed an index of annual market earnings changes against the annual earnings changes of individual firms. This model is of the form:

$$(1)\quad (y_t - y_{t-1}) = \alpha + \beta(x_t - x_{t-1})$$

Where y represents the annual earnings of the firm, x represents the market earnings index and t is a time subscript denoting a particular year. Also, α and β are estimated using historical data.

Similarly, Brown and Kennelly [1972] used the same model but applied it to quarterly instead of annual data. Henceforth, these will be referred to as the BB and BK models.

A priori, both the BB and BK models have strong points. First, both define the expected earnings in terms relative to the market's earnings. A possible strong point about this type of expectation is that it eliminates the effect of market fluctuations on the individual firm expectation. As long as a firm maintains a constant earnings relation to the market from period to period, there will not be an unexpected earnings.

On the other hand, both the BB and BK models do not explicitly model earnings performance of a firm relative to previous performance for the same firm. In other words, the times-series properties of earnings are not explicitly modeled. The BK also ignores the fact that firm earnings are seasonally correlated and therefore is likely to have a problem of auto-correlated residuals.

Unlike the bivariate regression models the univariate models ignore the firm's relation to the industry but explicitly model the time-series properties of the earnings number. Collins and Hopwood [1980] studied the major univariate time-series models found in recent literature. These include: (1) a consecutively and seasonally differenced first order moving average and seasonal moving average model (Griffin [1977] and Watts [1975]), (2) a seasonally differenced first order auto-regressive model with a constant drift term (Foster [1977]), and (3) a seasonally differenced first order auto-regressive and seasonal moving average model (Brown and Rozeff [1978, 1979]). In the Box and Jenkins terminology, these models are designated as (0,1,1) x (0,1,1), (1,0,0) x (0,1,0) and (1,0,0) x (0,1,1) respectively. In this study, they are referred to as the GW, F, and BR models.

Collins and Hopwood [1980] found that the BR and GW models produced annual forecasts more accurate than the F model. In addition, they concluded that they also did at least as well as the more costly individually identified Box-Jenkins (BJ) models. As previously mentioned, these models have not been all related to capital markets. Nor have they been compared to the multivariate models of BB and BK.

1.20 Diagnostic Statistics Relating to Appropriateness of the Univariate and Multivariate EAM

1.21 Sample Selection

Data pertaining to the sample of 267 calendar year firms was obtained from the Compustat quarterly and CRSP monthly tapes. For a firm to be included in the sample, it was required to have no missing EPS data for the 64 consecutive quarters beginning with the first quarter of 1962 and no missing returns data for the years 1974 through 1977. This provided a sample period from 1962 through 1977. The EPS number used was primary earnings per share excluding extraordinary items and discontinued operations, adjusted for capital changes. The return figure selected from CRSP included both a dividend and price component.

Note that, unlike previous research, all firms which met the survivorship test were retained for analysis. We define this group to be the population of interest and make no attempt to generalize to a larger number of years or group of firms. To use statistical testing to make inferences about a larger group of firms would be unwarranted because there is no reason to believe that firms which fail to meet the survivorship test are the same as those that do. In fact, *a priori* reasoning indicates that firms meeting the test are very likely to be larger and older than the average. Also attempting to generalize across all years would be unwarranted because structural changes in the economy might produce a shifting in the relative performance of different forecast methods. Even if this was not a problem, in order to generalize to all years, it would be necessary to obtain a reasonably large random sample of years. This is not posible because of limited data availability.

Since statistical testing is used for making inferences about a larger population and under the circumstances we felt that such inferences would be unwarranted, no statistical tests are presented in this paper. Instead, our goal is to present results for an entire population which is of interest in its own right.

1.22 Model Estimation

All of the foregoing models were estimated for all of the sample firms. The years of 1974 through 1977 were used as hold-out periods and were used in studying forecast accuracy and capital market performance. Therefore, the 267 firms were each modeled 16 times, once for each method using pre-1974 data (48 quarters in the base period) and again for each method (49 quarters in the base period) using all data prior to the second quarter of 1974, etc. (The BJ models were re-identified each quarter.) The result was that each model made predictions for four quarters into the future for each of the 16 base periods in the hold-out period. The use of the forecasts is discussed in a later section of this paper.

1.3 Summary of Diagnostic Statistics

Table 1 presents a summary of diagnostic statistics for all of the above models. The purpose of this table is to provide indications with respect to how well the models fit the earnings data. Therefore table 1 presents both residual autocorrelation and residual crosscorrelation (with the market earnings index[1]) statistics. The former are important because if the residual error at time t is correlated with the residual error at a previous time then it is possible to use this relationship to predict the error at time t and therefore improve the model. The same line of reasoning applies for the crosscorrelation between the residual and the market earnings index.

Table 1 also gives the average squared correlation (R^2) coefficients. These have had the usual interpretation as being the percentage of variation in the dependent variable accounted for by the model.[2]

[Table 1 about here]

The auto/crosscorrelation statistics represent the percentage of times (expressed as a decimal) that a given coefficient was significant given an alpha error of .05 for each test. For example, for the BB model the lag one autocorrelations were significant 5.17% of the time. Also, for this model, the crosscorrelations between the market earnings index at time t-1 and the model residual at time t were significant 14.91% of the time.

Inspection of the data indicates very serious specification problems for the BK and F models. For example, both models have significant fourth order (lag 4) residual autocorrelations over 50% of the time. These percentages are excessively high since, due to an alpha error of .05, we would expect approximately only a 5% rejection rate by chance. In addition, the BK model has severe crosscorrelation problems at an assortment of lags while the F model has crosscorrelation problems at the first few lags. As mentioned above these significant autocorrelations and crosscorrelations indicate that the model errors (residuals) are predictable and therefore the models are improvable.

A second indication of the data is that all of the univariate models suffer from excessive crosscorrelation at the first few lags. For example, the BR model has a 25.51% significance rate at lag 0 and approximately a 12% significance rate at the next 3 lags. These results indicate that the market earnings index can be used to predict the error of the univariate models. This implies that a multivariate time series model incorporating both the index and individual earnings series would be useful.

It should be noted that the BB model is based on annual data and its correlation significance tests were based on only 11-14 data points (annual changes). This is important since the standard error of correlation is roughly proportional to $\frac{1}{\sqrt{N-K}}$ where N is the number of data points and K is the lag. The result is that at lag 1 the autocorrelation must exceed .59 in absolute value (when the sample size is 12) for the test to reject; therefore, the BB individual tests have a lower power than other tests resulting in rejection percentages which are conservative.

In summary, the BK and F models appear to be very poorly specified while all of the univariate models appear to suffer from excessive crosscorrelation with the index. This implies that these models can be improved upon by generalizing them to transfer function models. This is described below.

2.0 A Premier Transfer-Function Model

Because of the diagnostic inadequacies in the above models, we identified a premier transfer function model.[3] By a premier model we mean one which is not individually identified for each firm but rather a single model is used for all firms. Previous research with univariate time-series models has found this approach more fruitful because of the problem of search bias (i.e., excessive random variation leads to the selection of a wrong model when identified on a firm by firm basis). In addition, Hopwood [1980] found the transfer function identification process suffers from the same problem, but to a higher degree.

Therefore, a transfer-function model was identified based on the average autocorrelations and crosscorrelations. The result was a model of the form:

$$(1) \quad y_t - y_{t-4} = \theta_0 + w_0(x_t - x_{t-4}) + \phi_1 n_{t-1} + \theta_4 a_{t-4} + a_t$$

where y_t represents earnings, x_t the market earnings index, n_t the noise series (computed as $n_t = y_t - y_{t-4} - \hat{\theta}_0 - \hat{w}_0(x_t - x_{t-4})$) and a_t the uncorrelated white noise residual series. Also $\{\theta_0, w_0, \phi_1, \theta_4\}$ are the model parameters which must be statistically estimated.

While (1) is generically referred to as a transfer function, it is technically correct that $\theta_0 + w_0(x_t - x_{t-4})$ is the transfer function while $\phi_1 n_t{-1} + \theta_4 a_{t-4} + a_t$ is the noise model. Note that the result is that the transfer portion of the model is a bivariate regression model on seasonal differences while the noise model is the BR model. Using the language of Hopwood [1980], θ_0 is a (Type 8) deterministic trend constant, w_0 is a (Type 9) input lag parameter, ϕ_1 is an (type 1) ordinary first order autoregressive noise model parameter and θ_4 is a (Type 6) seasonal fourth order seasonal moving average parameter. This model will henceforth be referred to as AM1 (author model 1). Also, a second model was theoretically derived based upon assumptions with respect to the earnings and index series. This model is derived in appendix 1 and will henceforth be referred to as AM2.

Table 2 gives the diagnostic statistics for both AM1 and AM2. Note that for both autocorrelations and crosscorrelations the models are fairly well specified. The crosscorrelations at lags 2 and 3 are slightly large but investigation found that these could be traced to a severe one quarter slump of General Motors Corporation which affected the index.

[Table 2 about here]

3.0 Application of the Models to the Capital Market

3.10 Design

The market model of the form:

$$(3) \quad E[\ln(1 + R_{it} - R_{ft})] = B_j \ln(1 + R_{mt} - R_{ft})$$

was estimated, where (2) is the Sharp-Lintner [Lintner, 1965] capital asset pricing model and R_{it} represents the return on asset i in period t, R_{mt} represents the return in period t and R_{ft} is the risk free rate of return in period t. The estimation was done using ordinary least squares regression and was done for each year in the hold-out period. The estimations were done in each case by including monthly data for the 5 years preceding the hold-out year.[4] The residuals from these models when applied to the hold-out years (up to and including the annual earnings announcement date), constitute abnormal returns. The market index used was the value weighted market index containing the dividend-price returns of all firms as supplied on the CRSP tape.

The next phase was to estimate the association between the unexpected annual earnings from the EAM's and the annual cumulative abnormal returns (CAR). (These were computed by adding the monthly returns.) This approach was outlined by Foster [1977] and is stated as follows:

> 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 the association is dependent on how accurately each expectation model captures the market's expectation......

Foster applied this approach assuming a long investment given that the unexpected earnings was positive and a short investment given that it was negative. He then proceeded to measure the abnormal returns for different forecast methods given this strategy.

Since Foster's research, there has been an increasing knowledge of the fact that, for purposes of measuring association, this approach can be improved upon. For example, Beaver Clarke and Wright [1979] showed that the magnitude of the unexpected earnings is an important determinant of the size of the associated abnormal return (also see Joy et al. [1977]). Furthermore, Ohlson [1979, p. 526] analytically demonstrated that under certain conditions, the private value of information "for a decentralized strategy was simply the average R^2 (per unit of time) between signals and residuals."

We therefore measured association via Spearman's rank correlation between the scaled ((Actual - Predicted)/Predicted) unexpected earnings of the individual models and the residuals (annual CAR) and averaged these results across the 4 hold-out years. We used rank correlation because the scaled unexpected earnings were not normally distributed.

3.20 Empirical Results

Table 3 presents the squared rank correlation data. Note that several models, previously not discussed, have been added. These are BKF, AM1F, AM2F and BBF. The postscript of "F" denotes that forecasts were based on predicted values of the market earnings index.[5] In cases without the postscript, the actual value of the index was used to form the forecasts.

[Table 3 about here]

The results indicate that the multivariate models (except the BK model) have a higher association than the univariate models. While the other multivariate models outperform the univariate models, the BB has the highest R^2 statistic of .12165.

The performance of the BB model is surprising since it uses the same data as the other multivariate models, but uses it in an annualized form. One might expect the aggregation from quarterly to annual form to produce loss of information. Also the BB model is estimated on only one fourth the amount of data as the quarterly univariate and bivariate models and from a statistical standpoint this resulted in a very small sample of 11 to 14 of data points. For example in the 12 year case there were only 9 degrees of freedom since there are 2 parameters estimated and an additional degree of freedom is lost because of differencing.

3.30 A Further Explanation of the Results

A natural question to ask is: Does the information captured by the BB model contain or alternatively overlap with that of other models? In other words, is the information measured in the non-BB models simply a subset of the BB-measured information? This question was addressed by measuring the partial rank correlation between the non-BB models' unexpected earnings and the abnormal return while holding the BB unexpected earnings constant.

The results of this procedure are presented in table 4. Note that in all cases the partial correlations are small and less than 2.5%. There appears, however, to be a discernible pattern. First, note that models with an "F" suffix have substantially smaller partial correlations than other models. Among the remaining models the BK and F models are the lowest at about 1.3% and 1.5% respectively. Recall that both of these models did very poorly on the diagnostic statistics. Finally, all other models are remarkably close with statistics near 2%. This implies that it might be possible to combine the BB with one of these models to form a model which incorporates both annual and quarterly data. Such a model would be complex and is the subject of further investigation by the authors.

[Table 4 about here]

4.0 Empirical Accuracy Results

The ability to predict annual forecasts from quarterly earnings was studied. Table 5 presents the accuracy results for these forecasts. Panel 1 gives the mean absolute percentage forecast errors where errors larger than 1 were truncated to 1.[6] The four columns represent the accuracy as the end of the year approaches. For example, the average error for GW made 4 quarters prior to the end of the year is .2683588; the average error for the GW made three quarters prior to the end of the year is .2173826. In all cases, realizations are substituted for forecasts as the year end approaches. Therefore, for example, the GW annual forecast 3 quarters prior to the end of the year is based upon the realized value of the first quarter's forecast plus the forecasts (made from the end of the first quarter) for the second, third, and fourth quarters.

[Table 5 about here]

Note that the results of panel 1 are fairly consistent with those of the capital market, and the multivariate models (with the exception of the BK model) provide the most accurate forecasts.[7] Again, the BB model places first and AM1 second. Panel 2 presents the same data, but for each forecast the 13 models are ranked (from 1 to 13) and the mean ranks are substituted for the mean absolute percentage errors. This ranking approach has the advantage of not depending on a particular error metric and also avoids the need to standardize by using a percentage error metric (and therefore, eliminates the need to truncate because of small denominators). Note that the results are fairly consistent with those presented above but in this case and AM1 places first and BB and GW are approximately tied for second place[8] (four quarters prior to year end).

5.0 Summary and Conclusions

This study investigated univariate and multivariate statistical models in the context of their relative ability to serve as a market earnings expectation model (EEM). Included were univariate time series models, bivariate regression models and two bivariate multiple time series (transfer function) models developed by the authors. The models were compared on: (1) how well they fit the data, (2) their ability to perform in a capital market context and, (3) forecast accuracy.

The results indicated on all three comparisons that a multivariate model is the more appropriate specification. In particular, it was found that the model of Ball and Brown and the authors' transfer function model (authors' model 1) outperformed all other models considered, including the univariate time series typically found in the literature.

Table 1

Diagnostic Statistics for the Multivariate Models

Residual 1		Decimal Percentage of Significant Correlations					
Autocorrelations		BB**	BK	BR	F	GW	BJ
	N	1335	5340	5340	5340	5340	5340
	1	.0517	.4092	.1285	.1236	0365	.0051
	2	.0404	.4330	.0661	.0384	.0710	.0026
	3	.0007	.1272	.0801	.1028	.1047	.0028
	4	.0007	.6386	.0273	.5419	.0165	.0039
Lag	5		.0391	.0367	.0242	.0436	.0451
	6		.2318	.0343	.0346	.0373	.0047
	7		.0079	.0142	.0107	.0167	.0028
	8		.4064	.0199	.0331	.0131	.0026
	9		.0051	.0041	.0037	.0051	.0019
	10		.0788	.0099	.0077	.0097	.0013
	11		.0007	.0034	.0017	.0054	.0021
	12		.1478	.0069	.0047	.0079	.0021
Residual cross-correlations with index							
	0	.0000	.0000	.2551	.3071	.2487	.2279
	1	.1491	.2543	.1225	.1906	.1335	.1120
	2	.0172	.4678	.1199	.1685	.1433	.1064
	3	.0000	.2539	.1223	.1751	.1303	.1037
	4	.0007	.0865	.1041	.1230	.0985	.0895
Lag*	5		.1983	.0590	.0629	.0612	.0536
	6		.3459	.0418	.0504	.0388	.0356
	7		.2105	.0504	.0661	.0466	.0461
	8		.1794	.0408	.0541	.0418	.0290
	9		.1867	.0281	.0300	.0277	.0228
	10		.2758	.0193	.0217	.0193	.0148
	11		.1384	.0281	.0361	.0288	.0270
	12		.1457	.0109	.0161	.0090	.0103
Ave R2		.2180	.1339	.3782	.2406	.3582	.4636
Ave BPQ		1.01	60.88	11.45	17.43	10.30	7.60

*based on the correlation between the index at time t-k and the residual at time t where k is the lag

**due to the small amount of data only 4 lags were estimated for the BB model

Table 2

Diagnostic Statistics for the Transfer Function Models

Decimal Percnetage of Significant Correlations

Residual Autocorrelations		AM1	AM2
	1	.0371	.0356
	2	.0833	.0773
	3	.0640	.0566
	4	.0257	.0285
Lag	5	.0354	.0343
	6	.0378	.0288
	7	.0167	.0165
	8	.0094	.0161
	9	.0056	.0064
	10	.0082	0073
	11	.0056	0030
	12	.0073	0058
Residual crosscorrelations with index			
	0	.0597	.0094
	1	.0938	.0858
	2	.1275	.1103
	3	.1339	.1088
	4	.0762	.0946
Lag	5	0590	.0607
	6	0414	.0418
	7	.0487	.0403
	8	0227	.0275
	9	0212	.0245
	10	.0212	.0199
	11	.0225	.0232
	12	.0103	0069
Ave R^2		.4723	.4562
Ave BPQ		9.838	9.444

Table 3

R^2 Statistics Correlating Unexpected Earnings With Abnormal Returns

Method	R^2	Rank
GW	.08061	9
F	.09212	7
BR	.09641	4
BJ	.09535	6
BJRI	.09535	5
BK	.05618	11
BKF	.05000	12
AM1	.10733	2
AM1F	.08056	10
AM2	.10166	3
AM2F	.08368	8
BB	.12165	1
BBF	.00961	13

Table 4

R^2 Partial Statistics Correlating Unexpected Earnings With Abnormal Returns

Method	Partial R^2
GW	.01940
F	.01471
BR	.02254
BJ	.02049
BJRI	.02045
BK	.01324
BKF	.00755
AM1	.01969
AM1F	.00940
AM2	.02269
AM2F	.00771

Table 5

Forecast Accuracy Results for Annual Forecasts

Panel 1: Mean absolute percentage errors

	Quarter relative to end of year			
	4	3	2	1
GW	.2683588	.2173826	.1578771	.1051430
F	.2647187	.2207263	.1679165	.1150845
BR	.2637726	.2176338	.1538439	.1054330
BJ	.2661199	.2249112	.1591848	.1031495
BK	.3168017	.2956922	.1818661	.1282741
BKF	.3065775	.2960997	.1805420	.1328549
AM1	.2553877	.2074785	.1539929	.1022656
AM1F	.2604290	.2084394	.1560703	.1046179
AM2	.2630281	.2136976	.1547860	.1035174
AM2F	.2619234	.2165094	.1550833	.1030651
BB	.2528364			
BBF	.5199242			

Table 5 Continued

Panel 2: Mean Accuracy Ranks*

	Quarter relative to end of year			
	4	3	2	1
GW	6.03895	4.03296	4.22022	4.10712
F	6.11086	4.32434	4.61199	4.74419
BR	6.16854	4.47640	4.29888	4.25843
BJ	6.21873	4.64719	4.52659	4.31049
BK	7.14082	5.47790	5.36479	5.27790
BKF	7.06592	5.67715	5.45094	5.61498
AM1	5.76727	3.86217	4.07491	4.05393
AM1F	5.96030	4.97753	4.11536	4.31011
AM2	6.09064	4.17978	4.17228	4.09963
AM2F	6.03146	4.34457	4.16404	4.22247
BB	6.05543			
BBF	9.33109			

*a smaller rank denotes a more accurate forecast

NOTES

[1]The market earnings index was computed as a weighted average of the individual firm EPS (excluding the firm being modeled).

[2]Care should be exercised in interpreting the R^2 values. This is because they represent the percentage of variation explained on the series as modeled. Recall that different models do not all use the same type of differencing. The univariate models use a seasonal difference while the BK and BB use a consecutive difference. Also the BB uses annual data where the other models use quarterly data. Also a higher R^2 for the BJ models may be due to "search-bias" (see Foster [1978, p. 104]) which means that while the BJ identification process produces better fitting models (due to the way it works) it may often choose inappropriate models because of random variation in the data. Aside from this problem the R^2 results of the BR, F and GW are consistent with the accuracy results of Collins and Hopwood [1980].

[3]For a detailed discussion of transfer function modeling see Box and Jenkins [1970] and Hopwood [1980].

[4]For 1974 there were only 4 years of data available for regression estimation.

[5]The index predictions were based on applying the F model to the index. This model was identified based on the sample data.

[6]Truncation was done because the error metric |(Actual - Predicted)/Actual| allows for a zero or near zero denominator and therefore an undefined or explosive number can occur.

Our analysis of the data revealed that truncation numbers larger than one gave unstable mean error rankings for the univariate versus multivariate models. Therefore to minimize the effect of outliers on the results we choose a value of one. Foster [1977] also used a value of one. Also the relative performance with a value of one is consistent with that based on a mean rank criterion which does not depend on the choice of an error metric. It is also consistent with the diagnostic and capital market results. Finally the percentage of truncation for models was about the same and averaged about 5% of the forecasts. The BBF model, however, had an incidence of about 3 times as high as other models.

[7]Note that the relative performance of the <u>univariate</u> models indicate that there is no advantage to be gained by performing the costly process of identification. This is indicated by that fact that the BJ does not do better than the other models. Also the F model has a larger error than the other univariate models in three of the four quarters. Finally the BR and GW models are very close. These results are consistent with those of Collins and Hopwood [1980].

[8]Note that the relative performance of the univariate mkodels here is somewhat consistent with that based on the mean absolute percentage error (MAPE) metric. Again there is no justification for the costly process of individual model identification. These results differ in that the GW model consistently performs the best whereas on the MAPE metric the BR model did better than the GW model for 2 of the 4 quarters.

[9]On our sample data ϕ' averaged .77 and ϕ averaged .67. Our analysis of diagnostic statistics indicated that the resulting model fits very well.

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APPENDIX 1

Deviation of Author Model 2

It is possible to derive a single input transfer function model for two series given that the ARIMA models are known for both series. This appendix derives such a model based on the assumption that the EPS series follows the BR process and that EPS index follows a first order autoregression process with a seasonal difference. The literature has shown that the first assumption holds well [Collins and Hopwood, 1980] and the second assumption was made based upon identifying the index model from the sample data.

Assume that the index series (x_t) follows a first order autoregressive model of the form (x_t and y_t will henceforth be assumed to be seasonally differenced)

(A1.1) $$a_t = (1 - \phi B)x_t$$

and the earnings series (y_t) follows the BR model

(A1.2) $$(1 - \phi' B)y_t = (1 - \theta B^4)a_t'.$$

Next add to the right hand side of (A1.1) a white noise series ℓ_t which is assumed to be independent of x_t. The result is

(A1.3) $$a_t = (1 - \phi B)x_t + \ell_t$$

Also (A1.2) can be solved for a_t' resulting in

(A1.4) $$a_t' = \frac{(1 - \phi')B}{(1 - \theta)B^4} y_t$$

Next substitute the right hand side of (A1.4) for a_t in (A1.3) giving

(A1.5) $$\frac{(1 - \phi'B)}{(1 - \theta B^4)} y_t = \alpha + (1 - \phi B) w_0 x_t + \ell_t$$

where α and w_1 have been added to correct for the fact that a_t' in (A1.4) and a_t in (A1.3) might be of different scale and correlated. Next multiplying both sides of A1.5 thru by $\frac{(1 - \theta B^4)}{(1 - \phi'B)}$ we obtain

(A1.6) $$y_t = \alpha' + \frac{(1 - \theta B^4)}{(1 - \phi'B)} (1 - \phi B) w_0 x_t + \frac{(1 - \theta B^4)}{(1 - \phi'B)} \ell_t$$

and assuming $(1 - \phi'B)$ cancels with $(1 - \phi B)$ (empirically we found these factors to be approximately equal[9]) we obtain the final model

(A1.7) $$y_t = \alpha' + (1 - \theta B^4) w_0 x_t + \frac{(1 - \theta B^4)}{(1 - \phi'B)} \ell_t$$

which can be written in more conventional form

(A1.8) $$y_t = \alpha' + w_0 x_t + \theta w_0 x_{t-4} + \phi' B n_{t-1} + \theta a_{t-4} + \ell_t$$

where n_t is the noise series.

The result is identical to AM1 but the term $\theta w_0 x_{t-4}$ is added to the model.