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Source: *The Journal of Finance*, Vol. 35, No. 1 (Mar., 1980), pp. 13-21
Published by: Blackwell Publishing for the American Finance Association
Stable URL: http://www.jstor.org/stable/2327177
Accessed: 27/11/2009 08:48

THE JOURNAL OF FINANCE • VOL XXXV, NO. 1 • MARCH 1980

On The Predictability of Corporate Earnings Per Share Behavior

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I. Introduction

RECENT RESEARCH ON THE predictability of corporate annual income numbers has indicated that in general such series are best described as essentially random processes. These results have been confirmed by many studies, Albrecht *et al* [1], Ball and Watts [2], Brealey [4], Lintner and Glauber [15], Watts and Leftwich [20], and have been widely cited in financial research (see Ederington [9]). The conclusions of these studies have major implications for financial theories which rely on assumptions of income predictability. Theories of corporate valuation that rely on growth and historical predictions thereof, such as those of Gordon [11] and Lintner [14], are based on questionable premises if such growth cannot be predicted. Notions of multi-period income-smoothing, which depend on predictable net income series, such as those of Barnea *et al* [3], and Gordon [12], are also likely to be incorrect in such an environment. These are non-trivial consequences and the findings have received considerable attention for this reason.

One limitation of the previous research is that the tests of predictability employed rely completely on extrapolatory or time-series models of annual EPS behavior (see all references above). The present research investigates the proposition that income numbers may have predictable properties when considered in their economic environment. To test this proposition, this study employs forecasting models utilizing economic lead-indicators to examine the predictability of annual EPS behavior. The methodology involves comparisons of the accuracy of one-step-ahead forecasts of individual firms' EPS numbers generated by alternative lead-indicator and extrapolatory models. The results indicate the existence of predictable (dependent) relationships between some economic lead-indicators and EPS numbers.

II. Alternative Forecasting Models of EPS Behavior

A. *The Research Hypothesis*

The basic research problem addressed in this study concerns the assessment of the predictability of EPS time series. The standard approach for assessing EPS predictability has been to compare the forecasting abilities of competing models using actual EPS data. See Brown and Rozeff [5], Watts and Leftwich [20], for examples. The types of models applied in such assessments have, however, been

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limited to extrapolatory or time series models. Conceptually, there is an alternative approach to the prediction of income behavior from historical data, namely, one that involves lead-indicator (or econometric) methods. Extrapolatory methods, by definition, model time series by identifying patterns in sequences of past observations of the dependent (forecasted) variable. In essence, these models assume that information concerning the future behavior of a time series can be found by examining its past behavior. Lead-indicator methods, on the other hand, use independent variables other than or in addition to previous observations of the dependent variable. Generally, lead-indicators are selected for their ability to predict future economic conditions rather than for their time series properties. Zarnowitz and Boschan [21], for example, list "smoothness" as a criterion for lead-indicator selection, but nonetheless note that the behavior of leading indicators is particularly volatile. It is therefore possible that an economic time series such as EPS could be predictable by lead-indicator models yet be so volatile as to be not predictable by extrapolatory methods. Considered in this context, it is apparent that the predictability of EPS time series cannot logically be established simply by examining the time series properties of EPS. It is necessary to examine the relationships between EPS and other information sets such as leading indicators before drawing conclusions on EPS predictability.

B. *The Forecasting Models Used*

In the present research, six alternative EPS forecasting models are employed to assess EPS predictability: three extrapolatory (including a random walk), and three lead-indicators. The extrapolatory models, chosen from a group of commonly-used forecasting models on the basis of superior EPS forecasting ability,[1] are:

1. An average growth model $\hat{Y}_{t+1} = Y_t + (Y_t - Y_{t-n})/(n-1)$
2. An exponential smoothing model $\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)\hat{Y}_t \; 0 < \alpha \leq 1$
3. A random walk model $\hat{Y}_{t+1} = Y_t$

In this study the average growth model uses ten previous observations of EPS to generate a nine-year average annual growth rate. Albrecht *et al* [1] found that a similar version of this model performed well in comparison to Box-Jenkins models in their EPS forecasting experiments. The smoothing constant in the second model is chosen by fitting the model to data for the ten year period immediately prior to each forecast, varying α from .1 to 1.0, with increments of .1, and choosing the α with minimum error. When α is unity in model 2, it is identical to model 3; however, (as shown below) its forecasting properties are not identical in the presence of noisy data. Both Ball and Watts [2] and Brooks and Buckmaster [6] found that versions of model 2 provided minimum overall fitting

[1] The models were chosen by the initial application of the alternatives to the sample. The models in the total group include: autoregressive, double exponential smoothing, exponentially smoothed first differences, autoregressive first differences, average growth in first differences and a random walk in first differences, as well as the three models in use at present. The estimating procedures and error measures are those described in Section III. Box-Jenkins models were not applied due to the restricted number of observations available for fitting. Potential improvements in the accuracy of the extrapolatory models may be available with large sample sizes, appropriate for such models, and attention is drawn to the qualification issued at the end of this section.

or forecasting errors in their EPS studies. Model 3 is included here not only for its predictive ability but also for its properties as a "costless" benchmark.

The lead-indicators used in the alternative models are chosen from the list of leading indicators of economic activity published in Business Conditions Digest [18]. The models themselves are extremely simple, as the construction of elaborate econometric models is considerably constrained by the limited degrees of freedom available. The models employed here forecast future EPS by multiplying the most recently observed EPS by growth rates computed as the percentage change in the selected lead-indicator over the fiscal year preceding the forecasted fiscal year. The lead-indicator models are:

4. A money supply model $\hat{Y}_{t+1} = Y_t(MS_t/MS_{t-1})$
5. A stock index model $\hat{Y}_{t+1} = Y_t(SPI_t/SPI_{t-1})$
6. A bank loan model $\hat{Y}_{t+1} = Y_t(BL_t/BL_{t-1})$

The money supply variable (MS_t) is the seasonally unadjusted $M1$. The stock price index variable (SPI_t), is the Standard and Poor's 425 Industrial index. The bank loan variable (BL_t) is the total dollar size of commercial and industrial loans by major banks, as compiled by the Federal Reserve. The measurement date for the leading indicators is taken to be the end of the month corresponding to the month of the fiscal year-end for Y_t, except for the money supply, for which the prior month value is used. These lead-indicator observations are available to the public when firms report annual earnings in the first calendar quarter subsequent to the fiscal year-end. Thus, at any time, they can be used for subsequent year forecasts. The earlier money supply figure is used because there is a two month delay in publishing the money supply figure for any given month.

It should be noted that this paper provides only a limited test of the comparative forecasting accuracies of all possible lead-indicator and extrapolatory forecasting models. Due care has been exercised in the present selection of models, but caution should be exercised when generalizing the results to other models. (See also footnote 1).

III. Sample Selection and Accuracy Measures

The 1978 COMPUSTAT tapes are used as the primary source of financial data. This provides a cross-section of firms for comparison, but limits the number of EPS observations to twenty per firm. Of the twenty observations, ten (the 1968–77 fiscal years) are used as the object of the forecasts of EPS made using the methods described in Section II. The sample firms are those firms on the November 1978 and May 1978 Expanded Annual Industrial file which are included in the Standard and Poors' 425 Industrial index, have December 31 fiscal year-ends, and have sales, operating income, and EPS data available for the years 1958–77 inclusive. These criteria produced a sample of 218 firms. The requirement that firms selected appear in the Standard and Poors' 425 index is enforced in order to insure a close association between the stock index used in the stock index lead-indicator model and the firms to which it is applied. The requirement that firms have a December 31 year-end biases the sample toward large industrial firms, and generally eliminates the retailing and food processing industries. These restrictions must be considered in the evaluation of the results.

The data for the extrapolatory models are drawn from two sources. Data for the end of November U.S. money supply and the end of December Standard and Poors' index are drawn from January issues of the Survey of Current Business [19], which are published on or about February 1. The bank loan data are drawn from the January Federal Reserve Bulletins [10], and are the reported figures for the last week in the previous December. These data are thus available to the public at the time that annual EPS results are announced.

To assess the predictive ability of the forecasts, two error measures are utilized. The first is the average absolute percentage forecast error, which computes the absolute percentage forecast error $|e|_{itj}$ for the forecast of EPS for the i^{th} firm in the t^{th} year using the j^{th} forecast model, denoted $\hat{Y}_{itj}$, as

$$|e|_{itj} = \left| \frac{\hat{Y}_{itj} - Y_{it}}{Y_{it}} \right|$$

Averages are taken over all i (218) firms and t (10) years producing an average composed of 2180 forecast errors for each of the j (6) models. In order to avoid biases arising from large individual outliers (or very small denominators), the maximum absolute single error is set at 200%.

The second error measure utilized is the rank-order of absolute forecast error by model for each firm. The problems of biassing outliers are avoided with this measure, as are the problems of distributional assumptions for hypothesis testing. With six alternatives, the average rank assigned will be 3.5. This value can be used as a benchmark in the evaluation of results.

IV. Statistical Analysis of Results

The forecasting models described above generated one-year-ahead forecasts of earnings per share (adjusted for splits and dividends, but excluding extra-ordinary items) for 218 firms for the years 1968–77. The average absolute forecast errors are presented for each model, by year and averaged over all years, in Table I. The most obvious feature of these results is the uniform size of the overall averages, which differ by a maximum of 2.6 percentage points. This is principally the result of the repeated use of the same sample in the determination of predictability.[2] The comparative sizes of average errors are of more interest. In terms of overall averages, the money supply model has minimum overall error, followed by the naive, stock index, average growth, exponential smoothing and finally the bank loan models. The year-by-year averages show a considerable variation in average error size (*cf* 1968 to 1975). Nonetheless the money supply model displays remarkable consistency in its comparative accuracy, generating the minimum average error in six out of ten years. Considered together, the money supply and stock index lead-indicator models are the minimum error models in nine of the ten sample years. The results indicate that lead-indicators have some ability to predict EPS behavior in an overall average sense.

To reduce the variance due to firm effects apparent in the overall results, the

[2] In a preliminary analysis of variance of these results, firm effects were found to account for over 90% of the sample variance.

Table I

Average Absolute Percentage Forecast Error by Model and Year

Model	68	69	70	71	72	73	74	75	76	77	Overall
Average growth	.1995	.2053	.3774	.3618	.2630	.2727	.3647	.4592	.3383	.2939	.3136
Exponential smoothing	.1849	.2125	.3427	.3536	.3000	.3158	.3846	.4218[a]	.3384	.3358	.3193
Bank loan	.1869	.2151	.4085	.3537	.2614	.2424	.3921	.5957	.3651	.3085	.3279
Money supply	.1842[a]	.2036[a]	.3562	.3524[a]	.2437	.2492	.3602[a]	.4582	.3232[a]	.2873[a]	.3018
Stock index	.2415	.2176	.3183[a]	.3564	.2318[a]	.2226[a]	.4155	.4333	.3660	.2993	.3102
Naive (random walk)	.1930	.2113	.3434	.3539	.2767	.2854	.3634	.4379	.3344	.2980	.3097

[a] Lowest average error for year.

average error in excess of the naive for each model is presented in Table II, along with certain sample statistics. These results indicate the significance of the differences in the overall averages of these differential model errors. Clearly the money supply model achieves the minimum error, as it has the only negative (smaller than naive) mean, and it is over five times its standard error. While the money supply, average growth, and bank loan models have different average errors, it is evident from the correlation matrix that their errors share commonalities in direction and size. The negative correlations indicated by the stock index model are unexpected. In particular, the three-way correlations among the bank loan, money supply, and stock index models are puzzling, considering that all three models use leading indicators of the same economy.

A robust test of the hypothesis that the mean errors rates of all models are equal is provided by Hotelling's T^2 statistic (see Scheffé [17], or Morrison [16]). Assuming that each firm's five-tuple of differential average error rates is an independent sample from a multivariate normal population with equal means, the T^2 statistic is distributed F (4,214) times a constant. The sample T^2 statistic of 453.81 is significant at an α in excess of .001, and indicates statistical significance among the mean differences. It is useful to note that Scheffé has shown that Hotelling's T^2 will be significant only if at least one statistical contrast among the model means is also significant, as determined by Scheffé's S or Hotelling's T test. A contrast produces a set of simultaneous confidence intervals for standardized mean differences between selected models with a joint confidence coefficient of $1 - \alpha$ for all possible contrasts. In light of the T^2 result, the computation of a contrast is logical.

The contrast of most interest at present is that between the mean difference of the money supply model and the other models' means. From the tables of the F distribution, we find that the T-statistic for a two-sided test of each element of the contrast is approximately 3.4238 for an α of .05 (using the F for 4 and 120 degrees of freedom to conservatively estimate F for 4 and 214). The results in Table II show that all but one of the mean differences are clearly significant, the exception being the stock index difference, which is affected by its large standard error.[3] In general, therefore, the parametric tests indicate that significant differences do exist between models' accuracies.

The tests and results presented to this point are based on assumptions of independence and normality of sample observations. Deviations from these assumptions can seriously affect the power of the tests. Rank order methods provide alternative tests of these hypotheses that do not require such strong assumptions. The average across firms of the rank of each model's average forecasting error per firm is presented in Table III, with selected test statistics.[4] The ordinal ranking of the size of the average ranks corresponds almost exactly to the ordinal ranking of the average errors presented in Table I. However, the

[3] A separate contrast of all mean differences against the stock index model produced no significant differences at all. These results contradict even the non-parametric tests given below, supporting the conclusion that the model's large standard error dominated the parametric tests.

[4] The non-parametric tests were also repeated on the individual observations, rather than on the averages of each firm's observations as reported below. The results are consistent with the aggregate versions, particularly concerning the differential accuracy of the money supply model.

Table II

Analysis of Differential Errors (Net of Naive Error)

	Mean	Std. Error
Average growth	.00382	.00258
Exponential smoothing	.00954	.00303
Bank loan	.01821	.00219
Money supply	−.00792	.00132
Stock index	.00050	.00427

Correlation Matrix

	Ave. Grow.	Exp. Smooth.	Bank L.	Mon. Sup.	Stk. Ind.
Ave. growth	1.0000				
Exp. smooth	.1337	1.0000			
Bank loan	.3808	.0993	1.0000		
Money supply	.6926	.0849	.5785	1.0000	
Stock index	−.0869	−.0595	−.4749	−.0043	1.0000

Hotelling T^2 and Scheffe S Statistics

T^2 (Overall) 453.807
F (Overall) 111.883

Money Supply Contrast

$T(\bar{X} - \bar{X}_{ms})$	5.423	5.369	11.818	—	1.879

Table III

Analysis of Rank Orders of Average Errors

Model	Average Rank	Dunnett's t-Statistic vs Naive Rank ($t_{.025} = 2.55$)
Average growth	3.53	1.599
Exponential smoothing	3.86	3.455
Bank Loan	4.37	6.283
Money Supply	2.42	−4.569
Stock Index	3.58	1.906
Naive	3.24	—

χ^2 for Freidman's analysis of variance on ranks (adjusted for ties) with 5 degrees of freedom = 134.27.

Tabulated χ^2, $\alpha_{.025}$ = 12.832.

apparent differential accuracy of the money supply model is accentuated by the rank orders.

To test the hypothesis that all models' ranks are equal, the χ^2 statistic for Friedman's analysis of variance on ranks is computed. The sample statistic is ten times the tabulated value of the χ^2 at a significance level of .025. Given this result, a comparison among individual ranks is indicated. An appropriate test is again a test of each model against a control, which in this case is logically the naive. A multiple comparison test of ranks against a control which maintains an experimentwise confidence level α is given by Hollander and Wolfe [13], and is based on the parametric test of Dunnett [7], [8]. Table III presents the t-statistics for the comparisons of ranks with the naive control, and Dunnett's tabulated value of t for five two-sided tests, with a multiple confidence level of .05, for a sample size of 120. The results of the non-parametric tests are consistent with the parametric results. The money supply has significantly lower ranks than any alternative model including the naive. The ranks of the average growth and stock index models are not significantly different from the naive ranks. The exponential smoothing and bank loan models are significantly worse.

The results of both parametric and non-parametric tests on the average errors of alternative forecasting models are thus consistent in their conclusions. Both reject the hypothesis that all forecast models are equal. Both indicate that a lead-indicator model, namely, the money supply model, is significantly more accurate than the alternative models presented here.

V. Conclusions

For the sample at hand, it is apparent that predictive information concerning the general behavior of annual EPS numbers existed over 1968–1977. These results should be considered preliminary as they are based on a limited sample of firms, of years, and of alternative forecasting models of both kinds. However, the fact that predictive information was derived from the simplest possible leading indicator models suggests that the development of more powerful leading indicator models of EPS may be possible. The unpredictability of EPS behavior appears open to question.

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