BEBR

FACULTY WORKING PAPER NO. 1027

Forecasting For the Electric Utility Industry: A Comparison of Alternative Models

E. L. Bubnys
D. H. Wort
J. K. Zumwalt

College of Commerce and Business Administration
Bureau of Economic and Business Research
University of Illinois, Urbana-Champaign

BEBR

FACULTY WORKING PAPER NO. 1027

College of Commerce and Business Administration

University of Illinois at Urbana-Champaign

March 1984

Forecasting For the Electric Utility Industry:
A Comparison of Alternative Models

E. L. Bubnys, Assistant Professor
Illinois State University

D. H. Wort, Assistant Professor
Illinois State University

J. K. Zumwalt, Associate Professor
Department of Finance

Abstract

Current financial difficulties faced by the Electric Utility Industry are a consequence of forecasting models developed over a decade ago. The Opec Oil Crisis of 1973-74 could not have been foreseen during the earlier modeling periods.

Using several statistical models, including the relatively recently-applied multivariate Box-Jenkins transfer function analysis, aggregate industry EPS and stock price are forecasted. One modeling period includes "pre-Opec" data; the second includes only data after 1973. The mean square forecast errors are found for each model and forecasting accuracy is thus compared.

FORECASTING FOR THE ELECTRIC UTILITY INDUSTRY:

A Comparison of Alternative Models

I. INTRODUCTION

The predictability of corporate earnings per share has received much attention in the finance and accounting literature. In the finance area, the prediction of corporate earnings is an important factor in the valuation of corporate shares for investment purposes and the prediction of EPS and/or the growth in EPS is frequently used in discounted cash flow models for estimating a firm's cost of equity capital. If EPS and EPS growth cannot be predicted, the appropriateness of the methodologies must be questioned. The issues presented in the accounting literature include the possibility of income "smoothing," the information content of reported accounting earnings and the extent to which share prices fully reflect publicly available information.

Earlier studies which have examined these issues have generally presented conflicting conclusions. That is, some studies have concluded that reported earnings are a random walk; some have reported that time series models indicate earnings can be predicted to some extent; some studies suggest the forecasts of financial analysts are no better than time series forecasts; and some studies indicate financial analysts forecasts are better than time series forecasts. It has also been suggested that the earnings of firms with stable earnings are reasonably predictable.

While none of the previous studies have focused on the electric utility industry, nowhere is the predictability of earnings more important than for the cost of equity estimation for an electric utility.

The most frequently used method of estimating the cost of equity capital is the discounted cash flow model which utilizes forecasts of future earnings/dividend growth. The methods used in these estimates include the extrapolation of past earnings, the extrapolation of historical retention rates and return on equity, and forecasts gathered from financial analysts.

The purpose of this study is to examine the predictability of earnings per share for the aggregated electric utility industry. (In future research the industry will be divided into groups based on each utility's commitment to nuclear power and the predictability of earnings for each group and each individual utility will be analyzed.) While previous research has shown that stock prices are unpredictable, the time series properties of a utility price index will also be examined. Section II briefly reviews previous research concerning the predictability of earnings. Section III presents the models to be tested in this research effort and Section IV presents the results. Conclusions are presented in Section V.

II. PREVIOUS RESEARCH

A Summary of Conclusions

The "Higgledy-Piggledy" growth studies by Little [18] and Lintner and Glauber [17] are among the earliest studies of the characteristics of earnings growth. Both of these articles concluded that earnings follow a random walk and that earnings changes cannot be predicted from previous changes. Cragg and Malkiel [12] and Elton and Gruber [13] reported results which indicate the forecasts of financial analysts are no better than time series forecasts and Ball and Watts [3] found that earnings appear to follow a submartingale or a "similar process."

However, other studies have reported results which conflict with the earlier studies. Brooks and Buckmaster [6] examined both aggregate and firm specific earnings data and reported that aggregate earnings appear to follow a submartingale but that "a substantial and identifiable portion of income time-series do not appear to follow a submartingale process."

Malkiel and Cragg [20] and Bell [5] both reported results which indicate analysts' forecasts are more accurate than the forecasts generated by time-series models. Brown and Rozeff [7] concluded that the forecasts of financial analysts were superior to the forecasts generated from earnings data alone. Chant [10] reported that the addition of economic environment variables improved the earnings forecasts of time series models.

The time series properties of quarterly earnings and time series models have been examined by several researchers. Lorek, McDonald and Patz [19] and Watts [22] reported significant seasonality in quarterly earnings data. In addition, Watts reported that "quarterly earnings are not independent but are related." Griffin [15] reached the same conclusion as Watts and suggested the time series properties of quarterly earnings might be characterized as a "first order autoregressive process in fourth differences" or a "first order moving average process in the first differences."

Collins and Hopwood [11] compared three time series models for predicting quarterly earnings and earnings predicted by financial analysts.

The three time series models are "(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 autoregressive model with a constant drift term (Foster (1977)), and (3) a seasonally differenced first-order autoregressive and seasonal moving average model (Brown and Rozeff (1978)). Collins and Hopwood utilized quarterly earnings forecasts from the Value Line Investment Survey to represent analysts' forecasts. A multivariate analysis of variance was used in the testing of the forecast errors of the four sources of earnings forecasts. Previous studies by Foster [14] and Brown and Rozeff [8] had used univariate testing methods. Collins and Hopwood concluded that the forecasts of financial analysts are superior to the forecasts of the time series models because the models were unable to respond as fast as analysts to such circumstances as strikes or sudden changes in earnings. They also concluded that earlier studies which found that financial analysts were unable to outperform time series models were due to a small number of outliers which caused the forecast errors to be large for all models.

Most recently Rozeff [21] compared long-term earnings per share growth rate estimates. The forecasts from six sources were used; a submartingale model, a comparison return model, a market adjusted returns model, the Sharpe-Lintner-Mossin asset pricing model, the Black zero beta model, and estimates from the <u>Value Line Investment Survey</u>. Rozeff concluded that (1) the comparison and market adjusted returns models were just as good as the submartingale model, (2) the SLM and

Black models were significantly more accurate than the submartingale model and (3) the Value Line estimates outperformed all the other models.

Also recently Abdel-Khalik and El-Sheshai [1] applied a Box-Jenkins methodology to the time series of sales at different levels of aggregation; the firm, the industry, and the total sample. They concluded that the (0,1,1)x(0,1,1) model provided the best forecasts for most firms and industries. In addition, they reported that a "statistically significant proportion of variation in forecasting accuracy was associated with the 'industry' factor..."

III. STATISTICAL PROCEDURES

This paper compares the forecasting abilities of different types of statistical models. The traditional econometric approach of building the structural model is the starting point. The ordinary linear least squares (OLS) approach implies a "causal" connection between the dependent and independent variables, as in equation one:

$$Y_t = \sum_{i=0}^{m} b_i X_{it} + a_t \qquad (1)$$

where $X_0 = 1$,

b_0 = the constant term,

$b_1, \ldots, b_m$ = the slope coefficients,

$X_1, \ldots, X_m$ = the regressors, and

a_t = the error term.

Due to the possibility of autocorrelation of residuals over time as a result of using level values for the variables, a second model was used.

The Cochrane-Orcutt iterative technique is commonly applied to correct for serial correlation. The form of this first order autoregressive model on the residuals is shown in equation two:

$$Y_t - \hat{\rho}Y_{t-1} = \sum_{i=0}^{m} b_i'(X_t - \hat{\rho}X_{t-1})_i + (a_t - \hat{\rho}a_{t-1}) \qquad (2)$$

where $\hat{\rho}$ = the correlation between consecutive residuals.

These structural models presume an a priori assessment of "causality." Time series models based on the works of Box-Jenkins [9], Granger and Newbold [16], and others assume no a priori structure between variables Y and X. The cross correlation function is the tool used in multivariate ARIMA to check for a reversed "feedback effect" of Y on X. This is analogous to the autocorrelation tool for single-series models. Several of the individual time series in this paper were tested using the univariate ARIMA model which involves an integration of an autoregressive (AR) process and a moving average (MA) process on a series which has been adequately differenced to achieve stationarity. Regular as well as seasonal parameters are possible. Equation three shows the form for time series Y:

$$\phi_p(B)\Delta^d Y_t = \Theta_0 + \Theta_q(B)a_t \qquad (3)$$

where $\phi_p(B)$ = a p order AR process with backshift operator,

Δ^d = the degree of differencing (d) in the series,

Θ_0 = a constant term, and

$\Theta_q(B)$ = a q order MA process with backshift operator.

The fourth statistical model used was the multivariate transfer function ARIMA technique. This technique, of which OLS regression is a special "white noise" case and Cochrane-Orcutt is an AR(1) autocorrelated case, determines the lag period for significant crosscorrelation between output and input series.

After each input series has had a univariate model fit to it, the output series is differenced to achieve stationarity. A prewhitening filter using the reciprocal of the input series' univariate model is applied to both Y and X. This "filters out" each series' same-correlatedness. The following cross correlation function between Y and X shows the significant lags of prior X observations affecting future Y observations. The crosscorrelation tool also measures the significance of "negative lags," whereby prior Y values affect future X values. The lack of such a feedback effect results in a one-way, or "Granger" causality. Specifically equation four shows the form of the multivariate model:

$$\Delta^d Y_t = \Theta_0 + \sum_{i=1}^{m} \left(\frac{\omega(B)}{\delta(B)} X_{i,t-b}\right) + \frac{\Theta(B)}{\phi(B)} a_t \tag{4}$$

where $\frac{\omega(B)}{\delta(B)}$ = the transfer function of zero, first or higher order,

b = the delay period before the first significant lag, and

$\frac{\Theta(B)}{\phi(B)}$ = the univariate model fit to the noise component (residuals) so as to achieve a non-autocorrelated ("white noise") process. The usual steps of identification, estimation, and diagnosis are taken for each model (uni- or multivariate) before any forecasting is conducted. The estimation procedure uses a non-linear technique (the Marquardt Algorithm) in order to minimize the sum-of-squared-errors function. In the multivariate case, each input series' transfer function and the noise component are estimated separately, and finally simultaneously to arrive at the final parameters.

The final forecasting model used was a composite of the OLS structural and ARIMA time series approaches. The structural, "causal" part of the model was estimated first, using the t modeling period observations. A univariate model was fit to the residual series. Forecasts were generated f periods in the future for the structural part ($\hat{Y}_{s,t+f}$) and added to forecasts of future residuals ($\hat{a}_{t+f}$). This model is represented in equation five:

$$Y_t = \sum_{i=0}^{m} b_i X_{it} + \frac{\Theta(B)}{\phi(B)} a_t. \tag{5}$$

IV. EX-POST FORECASTING METHODOLOGY

A total of 81 privately-owned electric utility companies are included in the sample. The Compustat tapes contain most of the data used in the models. The data used include the quarterly levels of (1) sales, (2) earnings per share--EPS--including and excluding extraordinary items, (3) total common shares outstanding, and (4) the end-of-quarter stock prices. The CRSP tapes are the source of the Fisher Index, a proxy for the market rate of return for each quarter. The Federal Reserve Bulletin is the source for the 91-day government treasury bill rate, the Consumer Price Index (CPI) which was used to construct the annualized inflation rate per quarter, and the Aaa utility bond rates. This latter series, the yield on new issues by Aaa-rated utility firms, was the proxy for long-term rates. It was deemed to be superior to the long-term government bond rate, which was altered from a 10-year to a 20-year maturity basis in 1976 and not usable for this study.

The Compustat data was averaged over the sample of 81 utilities for each quarter from the first quarter of 1972 through the first quarter of 1983. Thus 45 quarters of aggregate data, along with the Fisher index, the treasury bill rate, the Aaa utility bond rate and the inflation rate comprise the data used in this study.

The data were separated into two periods. The longer period, called the modeling period, comprised either the time frame first quarter 1972 - fourth quarter 1981 or only the post-oil embargo period first quarter 1974 - fourth quarter 1981. The four quarters of 1982 and the first quarter of 1983 comprised the ex-post forecasting period. Each of the equations presented in the previous section was estimated over both the longer and shorter modeling periods and then used to forecast the last 5 quarters of available data.

The criterion of forecast accuracy used to test the previously mentioned models is the mean squared forecast error (MSFE), expressed as:

$$MSFE = \frac{1}{n} \left[\sum_{f=1}^{n} (Y_{t+f} - \hat{Y}_{t+f})^2 \right]^{1/2}$$

where n = the number of quarters forecasted (5);

Y_{t+f} = the actual value of the variable f quarters ahead; and

$\hat{Y}_{t+f}$ = the f-quarter ahead forecasted value of Y.

Greater forecasting accuracy is implied by a lower MSFE, with zero implying perfect forecasting. There is no upper bound on MSFE.

V. THE RESULTS

EARNINGS PER SHARE

Table 1 lists the coefficient and parameter values of all models for EPS with and without extraordinary items. Table 2 lists the mean squared forecast error results for each model.

The Ordinary Least Squares Models

The OLS earnings-per-share models are bivariate, with sales per share as the sole explanatory variable. All the results for the two EPS variables in the two model periods show significant coefficients for per share sales. The adjusted R-squared values are reasonable. Not listed in the table are the severely low values for the Durbin-Watson statistic. These results implied definite positive autocorrelation difficulties, and led to the transformation of model variables using the Cochrane-Orcutt procedure. These results are also listed in Table 1. As before, the sales per share variables are significant. The adjusted R-squared values show an improvement over the previous models.

The ARIMA Models

Several univariate ARIMA models were developed for the earnings per share and price per share time series. The results are shown in the third panel of Table 1. The Compustat data included two EPS measures, one which included "extraordinary items" and one which did not. Both EPS measures were run over the 1972-81 period and the 1974-81 period. Seasonal (quarterly) differencing is evident in all four models, as well as a significant first order autoregressive parameter. Three of the models exhibit significance at the .05 level and one model shows significance at the .01 level.

The final panel in Table 1 lists the results from the transfer function multivariate ARIMA models. The earnings-sales bivariate models had significant contemporaneous (lag = 0) transfer coefficients. Thus sales per share during the same quarter had the only significant impact on EPS for the aggregated utility time series. The transfer coefficient was less significant for the longer 1972-81 modeling period. The noise components of the four models exhibited some variety. They included an AR(2) and AR(1) model on the residuals, as well as an MA(1) model and a white noise process.

The Mean Squared Forecast Errors

The models presented in Table 1 are used to forecast quarterly earnings for the five quarters from the first quarter of 1982 through the first quarter of 1983. The mean squared forecast error (MSFE) for each model is presented in Table 2. Several observations are in order. First, earnings per share without extraordinary items (EPS w/ox) exhibit lower MSFE's than EPS with extraordinary items. Second, in all instances except one, the post-OPEC oil embargo modeling period (1974-1981) exhibited lower MSFE's than the entire (1972-1981) period. Finally, and most importantly, the ARIMA models, both univariate and multivariate, outperformed the OLS models. The results of the combined OLS and time series models were similar to the results of the multivariate ARIMA for the 1972-1981 modeling period but exhibited a greater MSFE than the multivariate ARIMA for the 1974-1981 modeling period.

AVERAGE STOCK PRICES

Six different stock price models are examined. The per share sales and earnings variables are included as regressors in four of the models. An interest rate proxy is used as a third variable in each of these models. The short-term treasury bill rate and the rate on Aaa rated utility bonds are used as the short- and long-term interest rates, respectively. The Consumer Price Index is used as an annualized quarterly inflation rate and the Fisher Index is from the CRSP tapes.

The Ordinary Least Squares Models

The OLS and Cochrane-Orcutt adjusted OLS results are presented in Table 3. (Only the results for the entire 1972-1981 period are presented here. The results of the post-OPEC oil embargo period are similar.) Because the models are using the level of the utility price average as the dependent variable, the intercept is highly significant for all models. The sales per share variable is significant in all models except those which contain the Aaa utility bond rate as a long-term interest rate measure. The earnings per share variable is not generally significant, possibly due to high correlation with the sales per share variable. The short-term interest rate variable is not significant in either model, but the long-term interest rate variable is significant only for the unadjusted OLS model and the Fisher Index is only significant for the Cochrane-Orcutt adjusted models. The adjusted R-squared values are higher for the unadjusted OLS models in four of the six models.

The ARIMA Models

The results of the time series analyses are presented in Table 4. The univariate stock price time series, after first order differencing, exhibited white noise autocorrelation and partial autocorrelation functions. Since no AR or MA parameters were significant, the series itself is part of a random walk process. The predictive characteristic of such a model implies that the best forecast is the same as the most recent actual outcome.

The structural forms of the multivariate ARIMA stock price models are the same as in earlier tables. After first degree differencing on the output series, the number of significant transfer coefficients was smaller than for the OLS or Cochrane-Orcutt results. The Fisher Index and Aaa utility bond rate models resulted in strong coefficients. These were re-run as bivariate models and these results are also presented. Most of the transfer coefficients in Table 4 were estimated with zero lag due to evidence seen in the crosscorrelation function. Several exceptions included models numbered 4 and 6 (Fisher Index exhibited "spiked" crosscorrelation at lag = 5), and models numbered 5 and 7 (Aaa interest rate "spiked" crosscorrelation at lag = 1). However, only in the case of the Aaa rate did the transfer coefficient maintain strong statistical significance upon estimation.

With only the exception of model numbered 3, all noise components for the price output series models were parameterless--that is, white noise. This white noise feature is interesting, in the light of the strong autocorrelation which was present in the initial OLS results. Apparently, the first degree differencing on the output series together with the appropriate input series univariate models (not shown here) were enough to result in an uncorrelated residual series. This confirms the concerns expressed earlier regarding the use of level variables as several of the regressors.

The Mean Squared Forecast Error Results

Table 5 presents the results of the MSFE analysis. Overall, the results are mixed. None of the five methodologies clearly dominate the others. The small s denotes the method which results in the smallest MSFE. As can be seen the multivariate ARIMA and the combined OLS-time series model each exhibit the lowest MSFE for two of the models. The unadjusted OLS models and the adjusted OLS models each provide one of the lowest forecast errors.

V. CONCLUSION

This paper represents a first step in an examination of the predictability of earnings per share and prices in the electric utility industry. Future research will examine several other factors which impact on the earnings and price of electric utilities. Two major factors are the impact of a utility's commitment to nuclear power on the earnings and valuation. The second factor is related to the first in that the allowance for funds used during construction (AFUDC) represents non-cash earnings. The risk of nuclear facilities not being completed and the large amounts of AFUDC in the reported earnings may cause different models to be appropriate for different utilities.

In any case, there seems to be evidence that multivariate ARIMA models and combination OLS and time-series models provide better forecasts than regression or univariate time-series models.

REFERENCES

1. A. R. Abdel-Khalik and K. M. El-Sheshai. "Sales Revenues: Time-series Properties and Predictions." Journal of Forecasting, Vol. 2 (October-December, 1983), pp. 351-362.

2. W. S. Albrecht, L. L. Lookabill, and J. C. McKeown. "The Time Series Properties of Annual Earnings." Journal of Accounting Research, Vol. 15 (No. 2, Autumn, 1977), pp. 226-244.

3. R. Ball and R. Watts. "Some Time Series Properties of Accounting Income Numbers." Journal of Finance, Vol. 38 (June, 1972), pp. 663-681.

4. A. Barnea, J. Ronen, and S. Sadan. "Classificatory Smoothing of Income with Extraordinary Items." Accounting Review, Vol. 51 (No. 1, January, 1976).

5. F. W. Bell. "The Relation to the Structure of Common Stock Prices to Historical, Expectational and Industrial Variables." Journal of Finance, Vol. 29 (March, 1974), pp. 187-197.

6. L. Brooks and D. Buckmaster. "Further Evidence on the Time Series Properties of Accounting Income." Journal of Finance, Vol. 31 (December, 1976), pp. 1359-1373.

7. L. Brown and M. Rozeff. "The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings." Journal of Finance, Vol. 33 (March, 1978), pp. 1-16.

8. ________. "Univariate Time-Series Models of Quarterly Accounting Earnings per Share: A Proposed Model." Journal of Accounting Research, Vol. 17 (Spring, 1979), pp. 179-189.

9. G. E. P. Box and G. M. Jenkins. Time Series Analysis: Forecasting and Control, Revised Edition. San Francisco: Holden-Day, 1976.

10. P. Chant. "On the Predictability of Corporate Earnings Per Share Behavior." Journal of Finance, Vol. 35 (March, 1980), pp. 13-21.

11. W. A. Collins and W. S. Hopwood. "A Multivariate Analysis of Annual Earnings Forecasts Generated from Quarterly Forecasts of Financial Analysts and Univariate Time-Series Models." Journal of Accounting Research, Vol. 18 (Autumn, 1980), pp. 390-406.

12. J. G. Cragg and B. G. Malkiel. "The Consensus and Accuracy of Some Predictions of the Growth of Corporate Earnings." Journal of Finance, Vol. 23 (March, 1968), pp. 67-84.

13. E. J. Elton and M. J. Gruber. "Earnings Estimates and the Accuracy of Expectational Data." Management Science (April, 1972), pp. 409-424.

14. G. Foster. "Quarterly Accounting Data: Time Series Properties and Predictive-Ability Results." Accounting Review, Vol. LII (January, 1977), pp. 1-21.

15. P. A. Griffin. "The Time Series Behavior of Quarterly Earnings: Preliminary Evidence." Journal of Accounting Research (Spring, 1977), pp. 71-83.

16. C. W. J. Granger and P. Newbold. Forecasting Economic Time Series, New York: Academic Press, 1977.

17. J. Lintner and R. Glauber. "Higgledy-Piggledy Growth in America." In J. Lorie and R. Brealey, Modern Developments in Investment Management (New York: Praeger, 1972).

18. I. M. D. Little. "Higgledy-Piggledy Growth," Bulletin of the Oxford Institute of Economics and Statistics (November, 1962), pp. 389-412.

19. K. S. Lorek, C. L. McDonald and D. H. Patz. "A Comparative Examination of Management Forecasts and Box-Jenkins Forecasts of Earnings." The Accounting Review (April, 1976), pp. 321-330.

20. B. G. Malkiel and J. G. Cragg. "Expectations and the Structure of Share Prices." American Economic Review (September, 1970), pp. 601-617.

21. M. S. Rozeff. "Predicting Long-Term Earnings Growth: Comparisons of Expected Return Models, Submartingales and Value Line Analysts." Journal of Forecasting, Vol. 2 (October-December, 1983), pp. 425-435.

22. R. Watts. "The Time Series Behavior of Quarterly Earnings." Working Paper, Department of Commerce, University of Newcastle (April, 1975).

TABLE 1: A Comparison of Four Models Using
EPS with and without Extraordinary Items
(t-values in parentheses)

Model	Modeling Period	Statistics			
		Variables			
OLS		Intercept	Sales/share		$\bar{R}^2$
EPS w/x	72-81	0.234 (2.87)**	0.602 (4.40)**		.32
EPS w/x	74-81	-0.027 (-0.22)	1.000 (4.94)**		.43
EPS w/o x	72-81	0.226 (2.84)**	0.611 (4.59)**		.34
EPS w/o x	74-81	-0.38 (-0.31)	1.013 (5.21)**		.46
OLS Corrected for Autocorrelation					
EPS w/x	72-81	0.350 (9.02)**	0.405 (6.22)**		.51
EPS w/x	74-81	0.200 (2.77)**	0.635 (5.53)**		.51
EPS w/o x	72-81	0.337 (8.74)**	0.422 (6.53)**		.54
EPS w/o x	74-81	0.184 (2.60)**	0.658 (5.85)**		.54
Univariate ARIMA		d	Lag	ϕ Value	Model Variance
EPS w/x	72-81	4	1	0.404 (2.54)*	0.0023
EPS w/x	74-81	4	1	0.412 (2.27)*	0.0027
EPS w/o x	72-81	4	1	0.427 (2.71)**	0.0022
EPS w/o x	74-81	4	1	0.433 (2.41)*	0.0025
Multivariate ARIMA[a]		Sales/share		ϕ_1 Value	Model Variance
EPS w/x[b]	72-81	0.028 (2.16)*		0.318 (1.84)	0.0019
EPS w/x	74-81	0.039 (2.02)*		-0.319 (-1.70)	0.0025
EPS w/o x	72-81	0.033 (1.72)		0.373 (2.29)*	0.0021
EPS w/o x	74-81	0.038 (2.66)*		white noise	0.0024

*5% significance level

**1% significance level

[a]The Transfer Function Parameters are for lag = 0 and are differenced seasonally (d=4)

[b]For this model ϕ_2 = -0.389 and t_2 = (-2.24)*.

TABLE 2: Mean Squared Forecast Error For Earnings per Share For Five Forecast Quarters: First Quarter 1982 through First Quarter 1983

	EPS w/x		EPS w/o x	
Model	1972-81	1974-81	1972-81	1974-81
OLS	0.062	0.048	0.057	0.045
OLS (Corrected)	0.073	0.064	0.067	0.059
Univariate ARIMA	0.029	0.029	0.019	0.019
Multivariate ARIMA	0.033	0.017	0.027	0.019
Combined OLS & Time Series	0.036	0.034	0.025	0.028

TABLE 3: Results of Ordinary Least Squares Regression for the Utility Stock Price Index

(1972-1981 Modeling Period)

Model	Intercept	Sales per Share	Earnings per Share	Short-Term Rate	Long-Term Rate	Inflation Rate	Fisher Index	Adjusted R^2
1.	25.10	-16.37	8.19	-24.14	--	--	--	.42
	(10.71)**	(-2.77)**	(1.92)	(-1.53)	--	--	--	
2.	26.38	-16.88	7.54	--	--	-29.19	--	.49
	(12.31)**	(-3.77)**	(1.92)	--	--	(-2.81)**	--	
3.	26.00	-23.38	10.64	--	--	--	2.12	.39
	(11.10)**	(-5.20)**	(2.46)*	--	--	--	(0.77)	
4.	25.73	-11.31	7.18	--	-50.19	--	--	.45
	(11.59)**	(-1.69)	(1.72)	--	(-2.15)	--	--	
5.	18.41	--	--	--	--	--	-1.67	-.02
	(40.00)**	--	--	--	--	--	(-0.49)	
6.	25.94	--	--	--	-77.20	--	--	.43
	(18.32)**	--	--	--	(-5.50)**	--	--	
Cochrane-Orcutt Adjusted OLS								
1A.	28.85	-18.89	4.98	-27.16	--	--	--	.34
	(9.71)**	(-2.27)*	(1.71)	(-1.51)	--	--	--	
2A.	29.56	-23.29	6.58	--	--	-14.89	--	.37
	(10.74)**	(-3.57)**	(2.69)**	--	--	(-1.87)	--	
3A.	29.79	-27.42	8.23	--	--	--	3.55	.43
	(10.20)**	(-4.05)**	(3.35)**	--	--	--	(2.93)**	
4A.	29.59	-12.01	3.15	--	-58.74	--	--	.38
	(11.00)**	(-1.30)	(1.02)	--	(-1.99)*	--	--	
5A.	18.55	--	--	--	--	--	3.68	.16
	(19.36)**	--	--	--	--	--	(2.65)**	
6A.	28.04	--	--	--	-76.59	--	--	.34
	(11.99)**	--	--	--	(3.49)**	--	--	

t-values in parentheses.
*5% significance level.
**1% significance level.

TABLE 4: Results of Univariate and Multivariate ARIMA Models for the Utility Stock Price Index (1972-1981 Modeling Period)

Univariate Model	Model Variance
1. Random walk at first difference	2.316

Multivariate Models

	Sales per Share	Earnings per Share	Short-Term Rate	Long-Term Rate	Inflation Rate	Fisher Index	Noise Component	Model Variance
2.	7.81	-4.99	-22.01	--	--	--	white	2.044
	(2.55)*	(-1.97)	(-2.35)*	--	--	--	noise	
3.	5.95	-2.75	--	--	-22.60	--	Θ_1 = .432(2.65)*	1.524
	(4.00)**	(-1.99)	--	--	(-4.64)**	--	Θ_6 = .441(2.54)*	
4.	0.75	-1.45	--	--	--	9.52	white	1.254
	(0.34)	(-0.65)	--	--	--	(4.53)**	noise	
						-2.58[a]		
						(-1.89)*		
5.	5.93	-3.98	--	-127.93	--	--	white	1.610
	(1.32)	(-1.53)	--	(-4.19)**	--	--	noise	
		1.96[b]		-129.05[b]				
		(1.18)		(-3.80)**				
6.	--	--	--	--	--	8.98	white	1.356
	--	--	--	--	--	(4.43)**	noise	
						-2.44[a]		
						(-1.72)		
7.	--	--	--	-128.45	--	--	white	1.616
	--	--	--	(-4.32)**	--	--	noise	
				-130.25[b]				
				(-4.27)**				

[a] lagged parameter, lag = 5
[b] lagged parameter, lag = 1
*5% significance level
**1% significance level

TABLE 5: Mean Squared Forecast Error for the Utility Price Index: First Quarter 1982 through First Quarter 1983

Model	OLS MSFE	Adjusted OLS MSFE	ARIMA Univariate	ARIMA Multivariate	Combined OLS & Time Series
1	1.079	1.395	1.344	1.914	0.953s
2	0.535	1.011		0.312s	0.607
3	1.103s	1.357		1.878	1.144
4	1.445	1.813		0.615s	0.670
5	0.793	0.509s		1.197	1.107
6	1.712	1.822		0.931	0.584s

s = smallest mean squared forecast error.