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Neural network forecasting of quarterly accounting earnings[1]

Jeffrey L. Callen[a], Clarence C.Y. Kwan[b], Patrick C.Y. Yip[c], Yufei Yuan[d,*]

[a]*Department of Accounting, Stern School of Business, New York University, 40 West 4th Street, New York, NY 10012, USA*
[b]*Finance and Business Economics Area, Michael G. DeGroote School of Business, McMaster University, Hamilton, Ont. L8S 4M4, Canada*
[c]*Department of Mathematics and Statistics, McMaster University, Hamilton, Ont. L8S 4M4, Canada*
[d]*Information Systems Area, Michael G. DeGroote School of Business, McMaster University, Hamilton, Ont. L8S 4M4, Canada*

Abstract

This study uses an artificial neural network model to forecast quarterly accounting earnings for a sample of 296 corporations trading on the New York stock exchange. The resulting forecast errors are shown to be significantly larger (smaller) than those generated by the parsimonious Brown–Rozeff and Griffin–Watts (Foster) linear time series models, bringing into question the potential usefulness of neural network models in forecasting quarterly accounting earnings. This study confirms the conjecture by Chatfield and Hill et al. that neural network models are context sensitive. In particular, this study shows that neural network models are not necessarily superior to linear time series models even when the data are financial, seasonal and non-linear.

Keywords: Artificial neural networks; Quarterly earnings; Comparative forecast performance

1. Introduction

In a recent survey of artificial neural networks, Hill et al. (1994a) argue that the forecasting strength of neural network models relative to more standard statistical models may in fact be context specific and that neither approach clearly dominates the other. Their survey suggests, however, that artificial neural networks tend to forecast better than alternative statistical methods when the data are (i) of a financial nature (for example, Dutta and Shekhar, 1988; Bell et al., 1989; Odem and Sharda, 1990; Tam, 1991; Tam and Kiang, 1992; Donaldson et al., 1993), (ii) seasonal (Kang, 1991; Hill et al., 1994b) or (iii) non-linear (Donaldson et al., 1993).

The purpose of this paper is to compare the relative ability of neural network models and linear time series models to forecast quarterly

* Corresponding author.

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accounting earnings for a large sample of firms trading on the New York stock exchange. Quarterly accounting earnings satisfy all three of the above criteria since they are clearly financial and seasonal, and have been shown to be non-linear (Hopwood and McKeown, 1986; Lee and Chen, 1990; Callen et al., 1994). Although quarterly earning forecasts are of significant interest to managers, financial analysts, and capital markets researchers (Brown, 1993), they have as yet to be forecasted using artificial neural networks. By contrast, a number of accounting studies have forecasted quarterly accounting earnings using Box and Jenkins (1970) ARIMA models (for surveys of the literature, Hopwood and Newbold, 1980; Bao et al., 1983; Brown, 1993). The empirical evidence to date indicates that the parsimonious linear time series models developed by Foster (1977), Griffin (1977), and Watts (1975), and, especially, Brown and Rozeff (1979) dominate the forecasting abilities of other more general Box–Jenkins models (Bathke and Lorek, 1984). Therefore, this study compares the relative forecasting ability of these parsimonious linear models with the forecasting ability of artificial neural networks.

In his survey of artificial neural network forecasting, Sharda (1994) notes that many studies use one training sample and one validation sample in order to compare Box–Jenkins forecasts with forecasts from artificial neural networks. The results based on such comparisons, he concludes, "are subject to sample biases, and no statistical significance can be attached to such tests." In this regard, our study will provide a more comprehensive and valid comparison.

The paper is structured as follows. Section 2 briefly describes the data, the parsimonious linear time series quarterly earnings models, and the artificial neural network model. This section also describes how firm level forecasts are generated for both types of models. Section 3 compares the forecast accuracy of the neural model to that of the parsimonious linear models. Section 4 briefly concludes the paper.

2. Generating quarterly earnings forecasts

2.1. The data

Quarterly earnings per share data (before extraordinary items), adjusted for stock splits and dividends, were collected from the value line data base for 296 firms actively trading on the New York stock exchange. In addition to a December 31 year-end, the only other selection criterion dictated that each firm have a sufficiently lengthy time series of quarterly earnings per share data for estimation purposes, resulting in potential survivorship bias. In particular, the data had to encompass the entire period from the first quarter of 1962 until the first quarter of 1985; a total of 89 data points for each firm. Otherwise, firms are randomly chosen.

2.2. The linear models

The parsimonious linear time series models take the following forms:

$$\text{Brown–Rozeff} \quad (x_t - x_{t-4}) = \alpha + \beta(x_{t-1} - x_{t-5}) + \gamma\epsilon_{t-4} + \epsilon_t \qquad (1)$$

$$\text{Griffin–Watts} \quad (x_t - x_{t-4}) = \alpha + (x_{t-1} - x_{t-5}) + \gamma\epsilon_{t-4} + \delta\epsilon_{t-5} + \phi\epsilon_{t-1} + \epsilon_t \qquad (2)$$

$$\text{Foster} \quad (x_t - x_{t-4}) = \alpha + \beta(x_{t-1} - x_{t-5}) + \epsilon_t \qquad (3)$$

where x_t denotes earnings in quarter t, α, β, γ, δ and ϕ are parameters to be estimated and ϵ_t is random noise in quarter t. Of the three standard parsimonious models, the Brown–Rozeff is known to give more accurate forecasts on average (Bathke and Lorek, 1984). Therefore, to conserve on the description which follows, we focus on the Brown–Rozeff model. The approach is identical for the Foster and Griffin–Watts models.

The quarterly earnings forecasts from the parsimonious linear models are generated as follows. For each of the 296 firms in our sample, the 89 quarterly earnings time series are grouped

to form rolling samples of 40 quarters each in length. Using the first sample of 40 data points, α and β and γ in Eq. (1) are estimated by a standard maximum likelihood technique. The one-quarter ahead earnings forecast value for quarter 41 ($\hat{x}_{41}$) is obtained as

$$\hat{x}_{41} = x_{37} + \hat{\alpha} + \hat{\beta}(x_{40} - x_{36}) + \hat{\gamma}\hat{\epsilon}_{37} \tag{4}$$

where $\hat{\alpha}$, $\hat{\beta}$, $\hat{\gamma}$ and $\hat{\epsilon}_{37}$ are the estimated values of α, β, γ, and ϵ_{37}, respectively. Similarly, the second rolling sample of 40 quarterly earnings utilizes the data from quarters 2 to 41. Eq. (1) is re-estimated using the latter sample generating the one-quarter ahead earnings forecast $\hat{x}_{42}$.

Replicating this procedure for all of the data yields a total of 49 one-quarter ahead earnings forecasts ($\hat{x}_{41}, \hat{x}_{42}, \ldots, \hat{x}_{89}$) for each firm in the sample. A simple procedure is used to obtain the two-, three- and four-quarter ahead earnings forecasts. These forecasts will be compared to the forecasts obtained from the neural network model.

2.3. The artificial neural network model[2]

In order to generate one-quarter ahead earnings forecasts comparable to those of the parsimonious models, we also use rolling samples of 40 quarters in length each for the neural network approach. However, to facilitate learning by the neural network, each rolling sample is further broken down into 36 adjacent point 4-tuples of the form $(x_{t-3}, x_{t-2}, x_{t-1}, x_t)$ as inputs and 36 corresponding outputs of the form x_{t+1}. Thus, the first rolling sample consists of 36 inputs represented by the 4-tuples (x_1, x_2, x_3, x_4), $(x_2, x_3, x_4, x_5), \ldots, (x_{36}, x_{37}, x_{38}, x_{39})$ and their corresponding outputs $x_5, x_6, \ldots, x_{40}$. The subsequent rolling samples are treated in an analogous manner.

The neural network is structured to have an input buffer, a hidden layer and an output layer. The input buffer receives data from the 4-types of the form $(x_{t-3}, x_{t-2}, x_{t-1}, x_t)$. The output layer generates the single earnings number x_{t+1}. The hidden layer linking the input buffer and the output layer is used to capture the features of the input pattern. Although in general more than one hidden layer may be required to capture the details of the input features, we found one layer to be quite adequate for quarterly earnings.

We also tried and tested a number of different configurations of the neural network (such as simple or recurrent, altering the number of hidden nodes, and varying the type of transfer functions) and a number of different settings of the learning parameters (such as learning rate and learning time). The results reported here are based upon the best neural network forecasts.

The relationships among the three layers of the neural network are specified formally as:

$$\begin{aligned}
I_j^{[1]} &= \sum_{i=1}^{4} W_{ji}^{[1,0]} X_i^{[0]} + W_j^{[1]}, \\
X_j^{[1]} &= f(I_j^{[1]}), \\
I_k^{[2]} &= \sum_{i=1}^{4} W_{ki}^{[2,1]} X_i^{[1]} + \sum_{i=1}^{4} W_{ki}^{[2,0]} X_i^{[0]} + W_k^{[2]}, \\
X_k^{[2]} &= f(I_k^{[2]}), \qquad j = 1, 2, 3, 4 \\
&\qquad\qquad\quad k = 1
\end{aligned} \tag{5}$$

where

$X_j^{[s]}$ = the current state of the jth neuron in layer s ($s = 0$, the input; $s = 1$, the hidden layer; $s = 2$, the output),

$W_{ji}^{[s,r]}$ = the weight on connecting the ith neuron in layer r to the jth neuron in layer s,

$W_j^{[s]}$ = the bias of the jth neuron in layer s,

$I_j^{[s]}$ = the weighted sum of inputs to the jth neuron in layer s,

$f(z)$ = the transformation function, chosen to be the sigmoid function $(1 + e^{-z})^{-1}$.

[2] The neural network methodology is described in Rumelhart and McClelland (1986), Masson and Wang (1990), and Zurada (1992) among others. The microcomputer software used in this study is NeuronWork Professional II/Plus, V4.0, by NeuronWare, Inc.

Since the sigmoid function is bounded with $0 \leq f(z) \leq 1$, this necessitated bounding the earnings data to lie between 0 and 1. This was accomplished by linear transformations of the data of the form of $X_j^{[0]} = g(x_{t+j-4})$, for $j = 1, 2, 3, 4$, and $X_1^{[2]} = h(x_{t+1})$ for each input and output pair $(x_{t-3}, x_{t-2}, x_{t-1}, x_t)$ and x_{t+1} of the rolling sample, respectively. Specifically, for the rolling sample $H_u = \{x_u, x_{u+1}, \ldots, x_{u+39}\}$, the linear transformation function for inputs is specified as $g(x) = (x - a)/b$, where $a = \min(H_u)$ and $b = \max(H_u) - \min(H_u)$. In order not to constrain the forecast of x_{u+40} to be within the range imposed by H_u, we used the linear transformation function $h(x) = 0.2 + 0.6g(x)$ for the output.

If the W parameters in Eqs. (5) were known, four inputs would yield a forecasted output; that is, given $(x_{t-3}, x_{t-2}, x_{t-1}, x_t)$, Eqs. (5) together with the linear transformation functions would generate an estimate of x_{t+1}. Since the W parameters are not known, the neurons must be trained to estimate these parameter values, thereby establishing the correspondence between the inputs and the output. Using the first rolling sample, 10 000 random draws of the 36 4-tuples were employed in a standard back-propagation procedure that trains the neurons to adjust the Ws in order to reduce the forecast error (Rumelhart and McClelland, 1986, for a complete description of method). With a trained neural network, we forecast the one-quarter ahead forecast of x_{41} (denoted as $\hat{x}_{41}$) based on the input 4-tuple $(x_{37}, x_{38}, x_{39}, x_{40})$.

For the next rolling sample of 40 data points (which shares 35 common 4-tuples with the first rolling sample), adjustments of the Ws are made using the same adaptive learning procedure but with the number of random draws reduced to 1000 (2000 if the range of earnings in this rolling sample is not within 20% of the earnings range in the previous rolling sample). This procedure gives the value of $\hat{x}_{42}$. Repeating this process for all rolling samples provides the one-quarter ahead earnings forecasts $(\hat{x}_{41}, \hat{x}_{42}, \ldots, \hat{x}_{89})$ for each firm in the sample. The two-, three- and four-quarter ahead forecasts were obtained in a similar fashion.

3. Comparing quarterly earnings forecasts

For each of the parsimonious linear time series models and the neural network model, we first obtain 49 one-quarter ahead earnings forecast errors for each firm in the sample. To conserve on space, we report detailed results for the Brown–Rozeff and neural network comparison only. Mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean square deviation (MSD) metrics are computed for each firm. For the one-quarter ahead forecasts, these metrics are computed as:

$$\text{MAPE} = \frac{1}{49} \sum_{t=41}^{89} \left| \frac{\hat{x}_t - x_t}{\hat{x}_t} \right| \tag{6}$$

$$\text{MAD} = \frac{1}{49} \sum_{t=41}^{89} |\hat{x}_t - x_t| \tag{7}$$

$$\text{MSD} = \frac{1}{49} \sum_{t=41}^{89} \left(\frac{\hat{x}_t - x_t}{\hat{x}_t} \right)^2 \tag{8}$$

The reported MAPE and MSD metrics are normalized by the forecast. We also computed these metrics normalized by actuals and obtained similar results.

For the MAPE and MSD metrics, filters were used to eliminate outliers whenever $|\hat{x}_t|$ was less than the filter values (F). The filters took on the values \$0.025, \$0.05, \$0.075, and \$0.10. For the MSD metric, these filters exclude from 127 ($F =$ \$0.025) to 650 ($F =$ \$0.100) cases out of a total of 14 504 ($= 296 \times 49$) earnings forecasts for each model (i.e. from 0.9% to 4.5%).

Despite the potential for small filters to inflate the MSD and MAPE values arbitrarily, our results are quite robust across all filters. Therefore, only the cases $F =$ \$0.05 and \$0.10 are reported in Table 1.

The top panel of Table 1 compares mean MAPE, MAD and MSD values for all 296 firms in the sample for the Brown–Rozeff linear time series model (column (3)) and the artificial neural network model (column (4)). The Brown–Rozeff linear time series model consistently results in lower forecast errors by com-

Table 1
Relative one-period ahead forecast accuracy of the Brown–Rozeff (BR) linear time series model and the neural network model

(1) Forecast error metric	(2) Filter	(3) Mean forecast error: BR model	(4) Mean forecast error: neural network model	(5) Wilcoxon test statistic	(6) % neural network model dominant	(7) Binomial test statistic
All (296)						
MAD	None	0.23	0.25	10.7*	18.2	−14.1*
MAPE	0.05	0.44	0.51	7.84*	26.0	−9.41*
MAPE	0.10	0.38	0.45	9.69*	21.0	−12.3*
MSD	0.05	2.62	3.00	2.90*	38.2	−4.19*
MSD	0.10	1.35	2.27	4.52*	33.1	−6.18*
All but linear stationary at 1% significance (225)						
MAD	None	0.24	0.26	9.24*	17.8	−12.6*
MAPE	0.05	0.46	0.52	6.89*	25.3	−8.51*
MAPE	0.10	0.39	0.46	8.61*	19.6	−11.5*
MSD	0.05	3.14	3.29	2.26**	38.7	−3.49*
MSD	0.10	1.58	2.58	3.75*	33.8	−5.15*
Linear stationary at 1% significance (71)						
MAD	None	0.20	0.23	5.39*	19.7	−6.41*
MAPE	0.05	0.40	0.49	3.80*	28.2	−4.09*
MAPE	0.10	0.35	0.42	4.45*	25.4	−4.77*
MSD	0.05	0.96	2.07	1.93	36.6	−2.34**
MSD	0.10	0.61	1.27	2.65*	31.0	−3.46*

Two-tailed tests: *significant at the 1% level ((absolute) critical value = 2.58); **significant at the 5% level ((absolute) critical value = 1.96).

parison to the neural network model for all metrics and filters.

A Wilcoxon signed-rank test and a binomial test are used to determine the statistical significance of this result. The two-tailed Wilcoxon signed-rank test statistic based upon all 296 error metric pairs is reported in column (5) of Table 1. The Brown–Rozeff model significantly dominates the non-linear neural network model for all metrics and filters at the 1% level.

Column (6) in Table 1 reports the proportion of cases for which the neural network model dominates the linear time series model. This proportion is consistently less than 40%. Column (7) lists the one-tailed binomial test statistic based on the z-score

$$z = \frac{\hat{p} - 0.5}{[\hat{p}(1-\hat{p})/n]^{1/2}} \tag{9}$$

where $\hat{p}$ is the proportion of cases for which the neural network model dominates the Brown–Rozeff linear time series model, and n is the number of firms in the sample (296 for the top panel of Table 1). The test statistic is significant at the 1% level irrespective of the metric and filter, once more indicating the superior forecasting ability of the Brown–Rozeff model over the neural network model.

The 296 firms in the sample were further analyzed as to the (wide sense) stationarity and linearity of their quarterly earnings data. After transforming the data in a number of ways, first-order differencing was used to generate stationarity. Firms were classified as stationary if their (transformed) quarterly earnings exhibited time-invariant means and auto-covariances at the 1% significance level. More specifically, the constancy of the mean over N segments of the time series data ($N = 2, 3, 4$) was tested using a standard analysis of variance approach. The hypothesis of time-invariant auto-covariances was tested using the spectral approach developed by Priestley and Subba Rao (1969). Firms were

further classified as exhibiting linearity if their earnings time series satisfied the Subba Rao and Gabr (1980, 1984) linearity test at the 1% significance level (Callen et al., 1994, for more details). The 296 firm sample was then split into two subsamples: (i) firms which are stationary *and* linear and (ii) firms which are not.

The middle panel of Table 1 repeats the metric calculations and test statistics for the subsample of 225 firms that are either non-stationary or non-linear (or both). As is to be expected, the forecast errors are larger on average than those for the 296 firm sample since the earnings of non-stationary or non-linear firms are more difficult to forecast. Nevertheless, the overall results for this subsample are the same as before. The Brown–Rozeff linear time series model significantly dominates the non-linear neural network model for all metrics and filters.

The bottom panel of Table 1 repeats the same analysis for the subsample of 71 linear *and* stationary firms with similar results. Not surprisingly, the mean forecast errors of both models are much smaller for this subsample by comparison to the mean forecast errors of the two larger samples.

A number of studies found neural networks to be superior to statistical models in forecasting later periods of the forecast horizon (Kang, 1991; Tang et al., 1991; Hill et al., 1994b). Table 2 compares the MAPE forecast errors of the Brown–Rozeff and neural network models (using the filter $F = \$0.10$) for one-through to four-quarters ahead of the estimation period. As is to be expected, the further ahead the forecast period, the poorer the forecasts for all models. Again, based on the Wilcoxon and the binomial, the Brown–Rozeff model forecast errors are significantly less than those of the neural network model for all forecast periods. The results for other metrics and filters are similar.

Although no details are reported here, the results for the parsimonious Griffin–Watts model were qualitatively similar to the Brown–Rozeff. Only, the Foster model yielded significantly poorer predictions than the neural network model.

4. Conclusion

Despite the fact that quarterly earnings data are financial, seasonal and non-linear, the linear Brown–Rozeff and Griffin–Watts parsimonious

Table 2
One- to four-period ahead relative forecast accuracy of the Brown–Rozeff (BR) linear time series model and the neural network model

(1) Case (number of firms)	(2) Number of forecast periods ahead	(3) Mean MAPE#: BR model	(4) Mean MAPE#: neural network model	(5) Wilcoxon test statistic	(6) % neural model dominant	(7) Binomial test statistic
All (296)	1	0.38	0.45	9.69*	21.0	−12.3*
	2	0.45	0.53	8.44*	25.0	−9.93*
	3	0.49	0.58	9.11*	22.6	−11.3*
	4	0.52	0.63	9.77*	22.0	−11.7*
All but linear stationary at 1% significance (225)	1	0.39	0.46	8.61*	19.6	−11.5*
	2	0.46	0.54	7.63*	24.0	−9.13*
	3	0.50	0.58	7.57*	23.1	−9.57*
	4	0.53	0.63	8.41*	20.9	−10.7*
Linear stationary at 1% significance (71)	1	0.35	0.42	4.45*	25.4	−4.77*
	2	0.43	0.49	3.62*	28.5	−4.09*
	3	0.46	0.57	5.17*	21.1	−5.96*
	4	0.50	0.61	5.07*	25.4	−4.77*

Two-tailed tests: * significant at the 1% level ((absolute) critical value = 2.58).
MAPE# is calculated using the filter $F = \$0.10$.

time series models were found to yield better earnings forecasts than an artificial neural network model. In fact, the linear time series models were superior forecasters on average even for those firms in the sample whose earnings exhibited significant non-stationarities and/or non-linearities. These results buttress Chatfield's (1993, 1995) and Hill et al.'s (1994a) contention that the forecasting performance of artificial neural networks is likely to be context sensitive.

In a recent editorial, Chatfield (1995) decries the 'hype' surrounding neural networks and the bias against publishing negative results, especially concerning 'state-of-the-art' techniques. This study reports just such a negative result. In the context of quarterly accounting earnings, the performance of the neural network model was found wanting.

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Biographies: Jeffrey L. CALLEN is Professor of Accounting at the Stern School of Business, New York University and the Editor-in-Chief of the *Journal of Accounting, Auditing & Finance*. His current research interests include the time series properties of accounting data, financial contracting, noise in financial markets, and the economics of non-profit and regulated industries.

Clarence C.Y. KWAN is Professor of Finance and Chair of the Finance and Business Economics Area at McMaster University. He received his Ph.D. in finance from the University of Toronto. Professor Kwan's current research interests are in portfolio analysis, investments, and international capital markets.

Patrick C.Y. YIP is Professor of Mathematics and Statistics, and a member of the Communications Research Laboratory at McMaster University. His research interests include digital signal processing, transforms and transform algorithms, time series analysis and non-linear dynamical systems.

Yufei YUAN is Professor of Information Systems at the School of Business, McMaster University. He received his Ph.D. in Computer and Information Systems at the University of Michigan in 1985. His research interests include fuzzy logic systems, neural networks, genetic algorithm, and decision making in finance and health care.