DETECTING "REAL" NET EARNINGS USING INDIRECT PERFORMANCE MEASURES: A NEURAL NET ANALYSIS

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ABSTRACT

In the post-Enron era, much has been written about how investors can protect themselves against unscrupulous management and their self-serving manipulation of financial reports. One of the often cited concepts is the theory that true performance of a company can be evaluated by comparing net income over a period of years with operating cash flow over the same period of years. The theory continues that, if a company reports net income over a period of years, without an equal amount of operating cash flow, the net income is suspect. The purpose of this paper is to analyze the relationship of net income with a number of corporate performance parameters over time using neural net analysis. The results revealed a strong correlation between cumulative net income and selected financial variables which helps the investor to assess a firm's true performance.

INTRODUCTION

Earnings manipulation has been a constant and reoccurring problem throughout the investment community [2]. As a result there has been renewed interest in attempting to detect "real' earning via indirect means. One standard approach has been to use operating cash flow as a proxy for "real" earnings since, in general, operating cash flow over time is more difficult to manipulate than net earnings [1]. The basic notion is that firms reporting consistent positive earning over time without the corresponding positive operating cash flows are suspect and the investor should take notice. One of the key issues in using indirect methods for estimating "real" earnings is the timeframe. Typically, both earning and even cash flows can be manipulated in the short term. However, over longer periods the later is more difficult to distort. Another consideration in selecting an appropriate accumulation timeframe is the turnover of the senior management. A typical range is three to five years [4]. Accordingly, an accumulating time period of seven years should be adequate to ameliorate the "effects" of any earnings manipulations over several management teams. The purpose of this paper is to investigate the potential of using a number of indirect proxies for detecting "real earnings using both multiple regression and neural net technology.

DATABASE

The database consisted of selected financial data on the Fortune 100 Companies taken over a 7-year-period (1995 – 2001). Figure 1 presents a scatter diagram of cumulative net income versus cumulative operating cash flow. The corresponding linear correlation coefficient is 0.757. This result underscores the basic premise of this paper, namely, that cumulative operating cash flow might be a good predictor of cumulative income. However, there still exists a significant amount of variability that is unexplained by cumulative operating cash flow (R^2 = 0.57). Therefore, a number of additional variables were included in the analysis [**7**].

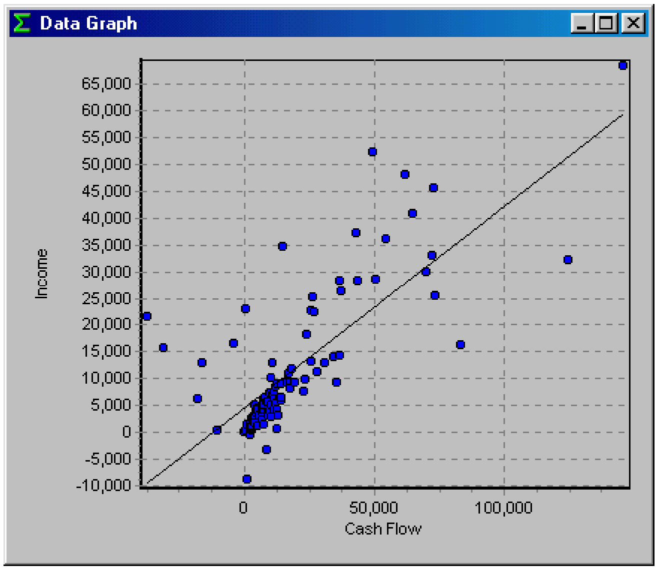

Figure 1 – Cumulative net earnings versus Cumulative Operating Cash Flows

Table 1 provides a summary of the variables included in this study. The target or dependent variable is cumulative net earnings over a seven-year period (1995-2001). The financial variables are reported in millions of dollars. As can be seen there is a wide variance among three of the corporate performance variates, e.g., debt change. Typically, this situation tends to challenge traditional methods of analysis like multiple regression.

Table 1 – Variable Descriptive Statistics

Variables	Mnemonic	Mean	Std Dev.
Cumulative Operating Cash Flows (7 yrs.)	Cash7	20,834	9,829
Debt Change (7 yrs.)	Ddebt	14,448	48,754
Assets Change (7 yrs.)	Dassets	56,701	125,510
Market Value Change (7 yrs.)	Dvalue	38,397	66,413
Industry Type (1=product, 0 =service)	Type	0.55	-
Cumulative Net Income (7 yrs.)	Earn7	12,643	5,017

NEURAL NETS

The architecture of an artificial neural net (ANN) consists, at a minimum, of two layers: an input neuron or neuron layer and an output neuron. There may also be one or more intermediate or "hidden" layers of neurons. It is these hidden layers of neurons and the complexity of the interconnections that increase the computational power of ANNs. In the most common schema, each neuron in one layer is connected to each neuron in the layer. For this analysis, the prediction of cumulative net earnings is derived as a function of input states and a set of weights. The specific input states include the factors reported in Table 1. The values for the input states may come from the activation of other neurons or specific environmental factors. The values for the weights and thresholds are determined through an iterative process with the goal of minimizing the aggregate error. This solution approach is called backward propagation that consists of two steps: forward pass for measuring errors and backward pass for updating the weights. Typically, a portion of the database is used to train the neural net and the remaining data is used for predictive or classification purpose. Neural nets, like multiple regression, are impacted by degrees of freedom. In some instances, adding more hidden layers can increase the degrees of freedom for a given database. Additionally, the size of the required database can be significantly smaller for an ANN especially if a large number of discrete factors are involved. ANNs have been found to be effective in analyzing complex non-linear application like corporate earnings [3], [5], [6], [8].

RESULTS ANALYSIS

A standard stepwise multiple regression analysis was conducted on the data set as a basis for comparison with the neural net analysis. The database consisted of 80 observations with a hold-out group of 20 observations. Table 2 presents the statistically significant variables and corresponding betas at the 0.05 level where the dependent or target variable is cumulative net income.

Table 2 – Statistically Significant MR Variables

Variable	**Beta**
Cash7	0.667
Dassets	0.412
Dvalue	0.271
Ddebt	-0.223

Not surprisingly, cumulative operating cash flow is the dominant variable in the MR model. Interestingly, the change in debt service variable shows a negative relation with the target variable. This suggests that as debt service increases cumulative net income decreases. The neural net model was run using the same database arrangement (80 observations for training and 20 for predicting). Figure 2 shows a graphic of the actual and predicted cumulative net income values for the training data set.

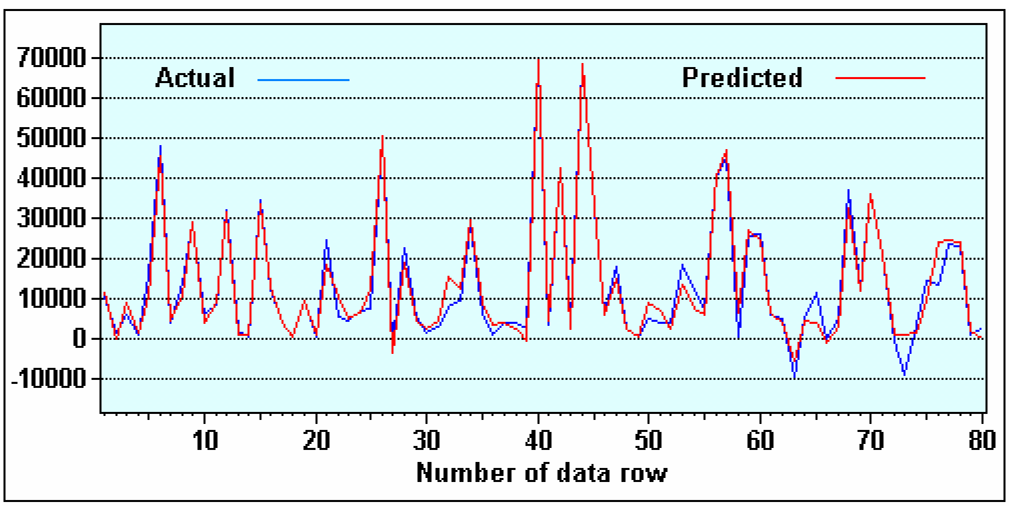

Figure 2 – Actual versus Predicted Values for Training Data Set (N=80)

Table 3 shows a comparison of model performance between the two modeling methods. The neural net yielded a larger R^2 for both the “in-sample” or model case and the “hold-out” or forecast case. Again, the “hold-out” group consisted of the same 20 observations. These results highlight the robust nature of ANNs especially in cases where the variance for some variables is large.

Table 3 Modeling Comparisons

Model	Model R^2	Forecast (R^2)
Neural Net	0.96	0.71
Regression	0.79	0

SUMMARY

There is a growing interest throughout the investment community for improved validation of corporate earnings reports. The purpose of this paper was to determine if operating cash flows along with related corporate financial data could be used to detect "real" cumulative net income. The results show that there is a strong positive relationship between cumulative operating cash flow and reported cumulative net income over a seven-year period. This relationship was further developed with the addition of other financial variables using both standard multiple regression analysis and neural nets. The neural net "out performed" the standard multiple regression model. The neural net yielded an R^2 of 0.96 for the 80-observation training group and 0.71 for the 20-observation holdout group. The application of neural nets for monitoring net income reporting holds much promise. Specifically, using a neural net model based on corporate financial parameters that are less immune to management manipulation can offer potential investors a truer picture of actual earnings performance.

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