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Owen P. Hall Jr.
Pepperdine University

Charles J. McPeak
Pepperdine University

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Owen P. Hall, Jr.
Pepperdine University

Charles J. McPeak
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ABSTRACT

It is a rare day when the Wall Street Journal does not include an announcement that a company is taking a restructuring charge. Nowadays it is often assumed that this charge is being taken for the purpose of managing earnings. The problems associated with earnings management are not limited to Wall Street but can be found throughout the world's financial markets. Ongoing developments in artificial intelligence technology hold considerable promise for helping monitor and detect financial fraud and abuse. The objective of this paper is twofold: first, to illustrate how neural nets, a branch of artificial intelligence, can be used to analyze the impact of corporate restructuring announcements on stock performance and second, to propose the need for a balanced approach using both tighter accounting standards and ex-post analysis for better control of excessive earnings management practices.

INTRODUCTION

A company taking a restructuring charge will record an expense, generally an estimate, and will set up a reserve for a like amount. A classic example is the technique used by a firm when it sells an operating unit. It is very likely that the sale will result in a one-time gain that could cause a spike in earnings. To avoid this, the firm will record a restructuring charge in an amount that approximates the gain. The charge will be an estimate of future expenses that could be incurred as a result of the restructuring action. In the short term earnings will go down. However, the firm may be engaging in earnings management, which is designed to increase earnings in the future and thus drive up the stock price. This timing has been linked to when CEO's stock options can be exercised (Safder, 2003).

In this regard, the primary legacy of former SEC Chairman Arthur Levitt is the war he waged on earnings management. Recent developments at Enron, Worldcom and Arthur Anderson underscore the fact that the earnings management war is not over. The market losses for the top ten firms re-issuing earning statements in 2000 exceed $25 billion (Wu, 2001). Seven out of ten of these restatements were directly linked to problems involving revenue recognition. Furthermore, the number of public companies having to make earnings restatements increased nearly 50% from 1998 to 2000 (O'Connor, 2002). The SEC has issued Staff Bulletin No. 101 (Heffes, 2001) that is designed to tighten accounting standards regarding revenue recognition. A basic principle of the new guidelines is that revenue should not be recognized until it is "realized and earned" (Griffin, 2001). Obtaining insight into how the market reacts to corporate restructuring announcements can directly impact current public watchdog operations as well as help in the formulation of new accounting guidelines and policies.

Neural net technology, a branch of artificial intelligence, is seeing increased usage in a variety of financial applications (Baesens, 2003;Young, 1999). Recent survey data indicates that over one-half of these applications involved stock market forecasting (Fadlalla, 2001). Neural nets are well suited for detecting the presence of earnings management via stock price fluctuations since they do not require prior assumptions about possible relationships between the firm and the market. This paper consists of three parts: 1) a review of the relevant literature; 2) a brief review of neural nets; and 3) a neural net analysis of a database gleaned from corporate restructuring announcements.

BACKGROUND AND LITERATURE

The literature is rich regarding earnings management, in general, and restructuring announcements, in particular, as a corporate strategy (Chai, 2002; Dechow, 2000; Grant, 2000: Payne, 2000). In broad terms, earnings management is defined as the judgmental actions taken by the corporate leadership regarding financial transactions with the intent of misleading stockholders and markets as to the actual economic state of the firm. The pressures to manage earnings are usually not in response to a single condition but to a variety of internal and external forces. Specific examples are access to debt markets, management compensation, poor planning and competition. For example, many firms use debt for funding both short term and long term investments. Typically, in setting a firm's credit worthiness the debt rating agencies utilize performance data including earnings reports. Accordingly, a decline in earnings or negative future earnings expectations could result in a drop in the firm's debt rating. Such occurrences in turn could increase the firm's cost of capital and thus reduce the prospects for new debt issues. The primary strategies used to manage earnings are revenue recognition and restructuring charges (Healy, 1999). Other techniques used to manage earnings are:

- ***Realizing one-time gains and one-time losses in the same period*** - Suppose that a company has a one-time gain from a settlement with the IRS. The company might record pending one-time losses in the same period.

- ***Matching Principle*** - This accounting principle requires that revenue be recorded in the same period with all costs incurred to generate that revenue. A company might capitalize expenses, thus putting them on the balance sheet, claiming that the expenses are related to future earnings. The capitalized expenses will thus be delayed until future periods.

- ***Big Bath Accounting*** - If a company faces a period with poor operating income, or if it faces the need to do a write-off, the company may consider that period to be a lost cause and take substantial write-offs in several areas. This technique might be used to disguise operating expenses, or it might be used to pull operating expenses from future periods into the current period, thus boosting future earnings.

- ***Depreciation*** - By changing depreciation to a longer period or a shorter period, the company can increase, or decrease earnings in a given period.

While earnings management is a major factor behind the current corporate scandals, the ability to analytically detect this behavior is somewhat uneven (Peasnell, 2000: Bunsis, 1997). Some of the reasons behind this lack of consistency can be attributed to variations in the length of the study event horizon, difficultly in characterizing the nature of the write-offs and uneven responses by the market. In general, one of the difficulties in detecting earnings management is a lack of specific definitions and metrics (Mulford, 2002). Earnings management is not limited to US markets but has seen wholesale use on a worldwide basis (Maijoor, 2002). Recent evidence indicates that firms operating in developed markets with strong accountancy practices tend to exhibit lower levels of earnings management than those with concentrated ownership and weak investor protection mechanisms (Leuz, 2003). While these observations are not surprising they do underscore the importance of independent and high quality accounting standards. However, the promulgation and use of such standards and procedures does not guarantee that earnings management will pass from the corporate playbook. This is because tighter accounting procedures may not be universally applied and management can still influence many of the accounting decisions. Therefore, an additional control element should be considered that involves the ex-post analysis of corporate actions. A key ingredient in this balanced approach is the use of analytical computer models like those being applied to a broad range of similar information technology applications (Liang, 2002; Thornett, 2001).

Along these lines, neural networks have seen increased use in the analysis of earnings management (Eakins, 2003; Safer, 2002). Specifically, neural nets appear as the analytical tool of choice when the variable data range is large and the underlying relationships between variables are somewhat ill defined as in the case of most firm-to-market transactions (Calderon, 2002). Figure 1 shows the base design concept that links technology (neural nets), accounting practices and corporate performance. This stratagem provides a multi-dimensional approach for the ongoing monitoring and detection of earnings management.

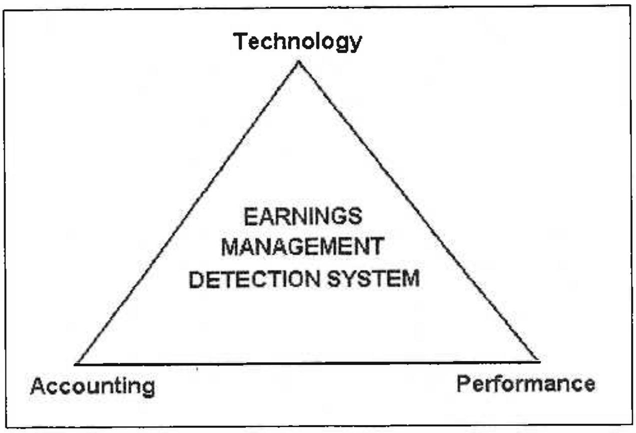

Figure 1 - Earnings Management Detection Scheme

NEURAL NETS

Artificial Neural Networks (ANNs) are a branch of artificial intelligence that addresses the problem of analyzing and forecasting data by simulating the biological neural network found in the human brain. First proposed in 1947, ANNs use complex network relationships to mimic the connections between sets of data. Among other things, ANNs have the advantage of not requiring prior assumptions about possible relations, as is the case with traditional analysis methods, e.g., regression. The architecture of an 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 above it as shown in Figure 2. In this example, the prediction of stock change is derived as a function of input states and a set of weights. The specific input states are the following: 1) the dollar amount of the restructuring charge, 2) reason given for the restructuring action and 3) the asset base of the firm at the time of the restructuring announcement. The values for the input states may come from the activation of other neurons or specific environmental factors, e.g., changes in the DOW. The example numerical value inside the node represents the threshold value for firing or activating the neuron. In this case, if the sum of the weights exceeds 1.5 then the neuron is "fired" which suggests a certain level of change in stock price. The values for the weights and thresholds are determined through an iterative process with the goal of minimizing the aggregate error. Typically, a portion of the database is used to train the neural net and the remaining data is used for predictive or classification purposes.

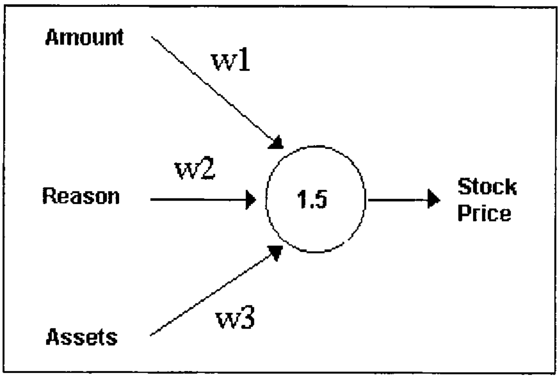

Figure 2 - Example Predictive Neural Node

Figure 3 illustrates two different possible neural net configurations. The first arrangement consists of two hidden layers while the second has one. The use of hidden layers is how ANNs handle complexity and uncertainty and are why they are particularly well suited for addressing complex financial issues like those found in restructuring announcements. Neural net models, 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.

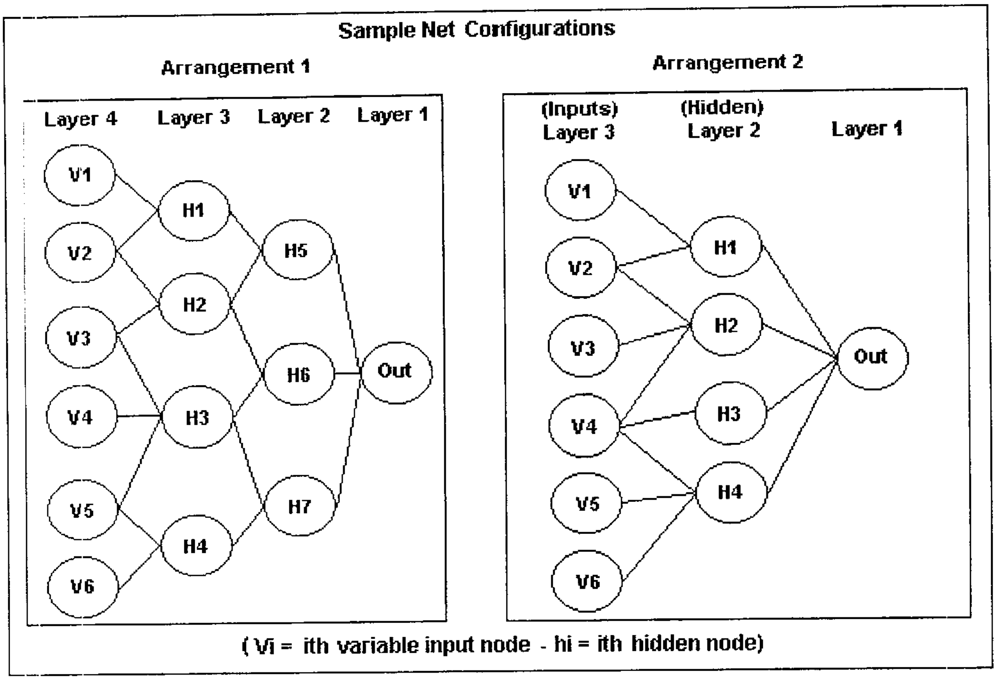

Figure 3 – Example Neural Net Configurations

Nevertheless, the most common configuration reported for financial applications, approximately 75%, is a single hidden layer (Fadlalla, 2001). This propensity to use a single hidden layer can be attributed to both limits in some of the neural net software packages as well as the general interest in avoiding model specification, i.e., indicating the number of hidden layers. Neural network analysis has shown a consistent pattern of outperforming many traditional statistical approaches in financial modeling (Fadlalla, 2001). This can be attributed to the fact that most financial structures are highly non-linear in nature.

DATA BASE

A sample database was developed from a thorough review of public announcements of corporate restructuring charges from July 1998 to August 1999. Specifically, the Dow Jones database was searched for articles with "Restructuring Charges" in the title. This review yielded 81 observations. A database was then assembled based on a variety of corporate performance and classification factors that are typically associated with predicting stock returns (Francis, 2003). The data variables and selected descriptive statistics from the database are summarized in Table 1. The percentage changes for stock price, the Dow and the NASDAQ are based on the day before and the day after the restructuring announcement. A six-month event horizon was selected since this mid range time period has not seen much previous analytical attention and represents perhaps an upper limit on the event horizon in terms of ex-post actions by the SEC. For example, if an ongoing neural net analysis by the SEC detects that certain firms appear to be engaging in earnings management then the SEC could take appropriate action.

Variable Description	Mean	Standard Dev.
Firm Type (1 = service, 0 = manufacturing)	0.25	0.43
Write-off Amount ($MM)	100.1	198.5
Reason (1= facility closure, 0 = other)	0.38	0.49
Stock % - Day	-0.57	5.58
Dow % - Day	0.03	1.02
NASDAQ % - Day	0.28	2.09
DOW % - 6 months later	9.59	10.50
NASDAQ % - 6 months later	34.67	21.96
Micro-Cap	0.40	0.49
Small-Cap	0.17	0.38
Assets ($MM)	4,262	6,885
Sales ($MM)	4,933	8,173
Stock % – 6 months later	7.61	45.50

Table 1 - Variable Statistics

These descriptive statistics show that approximately 25% of the sample consisted of service related firms and that 38% of the restructuring announcements involved facility closures. Additionally, 40% of the firms were classified as micro-cap, that is with a market capitalization less than $300 million. The average return for the stocks six months after the company announcements was 7.6%.

The standard approach for examining the impact of corporate pronouncements or actions (e.g., restructuring announcements) on stock prices is via the so-called event-study methodology (Barber, 1997). This approach focuses on the calculation of two statistics: AAR (average abnormal return) and CARR (cumulative average abnormal return). The abnormal rate of return (AR) six months after the restructuring announcement was selected as the dependent or target variable.

The AR was determined by subtracting the expected return from the actual reported return. The expected return was based on a linear regression of the rate of return for the individual stock versus the rate of return for the SP500 as illustrated below:

$$R_{it} = (a_i + b_i * SP500_t) \qquad (1)$$

where R_{it} is the rate of return for the security i for event day t and $SP500_t$ is the average market return. This relationship was then used to estimate the expected return for each stock six-months after the announcement using a 21-day average of the rate of return for the SP500 six months later. The statistics for the target variable (AR) reveal an average increase of 1.4% with a standard deviation of 45%. The data values for the target variable ranged from –92% to 172% over the six-month period. This very large range tends to challenge most methods of analysis, e.g., multiple regression.

ANALYSIS

As a benchmark, a standard stepwise multiple regression analysis of the database using abnormal return (AR) as the dependent variable was performed. This analysis yielded the following observations:

- None of the variables listed in Table 1 were significant at the 0.05 level with change in stock price six-months later. The p-values for the independent variables were 0.25 or larger.
- The amount of the restructuring charge is statistically related to whether facilities were being closed (r=0.24, p-value =0.023).
- The amount of the restructuring charge is statistically related to the asset base of the firm (r = 0.39, p-value = 0.000).

Against this benchmark a neural net prediction model was developed based on a "training" set of 70 observations randomly selected from the database, again using AR after six months as the target variable. This model employed a single hidden layer. The resultant R^2 was 0.88. This suggests that the ANN explained nearly 90% of the variability in AR. Figure 4 shows a plot of the actual versus predicted AR values for the training database. On the one hand, the graphic illustrates the neural net's ability to accurately track the actual measurements.

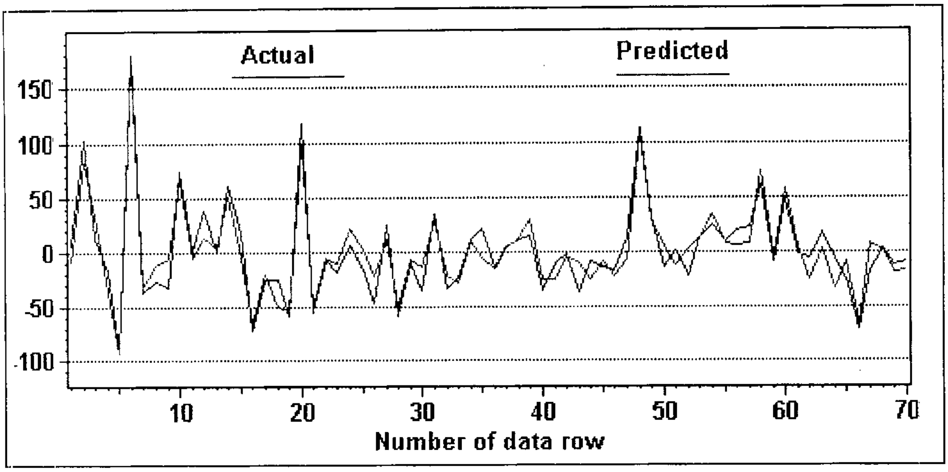

Figure 4– Actual versus Predicted AR Values Using Training Database (N=70)

On the other hand, this plot underscores the wide variation in the AR values that represents a significant challenge to accurate prediction using a holdout group from the database. The trained model was then evaluated for its predictive performance using the holdout group of

11 observations. The corresponding R^2 was a negative 0.82. Negative R^2's are possible when using a holdout group as the base. These results indicate that the developed ANN model did not detect a pattern between the predictor variables and the target variable using the holdout group. This lack of detecting the impact of restructuring on stock prices 6 months later can be attributed to the fact that other factors may have intervened over this period.

Neural nets can also be used for classification analysis wherein the target variable is characterized into two or more categories. An example is consumer credit analysis where the target variable categories are good credit, average credit and poor credit (Baesens, 2003). A two category classification analysis was performed on the assembled database with respect to identifying "winners – stocks with a positive AR after six months" and "losers – stocks with a negative AR after six months" using an ANN classifier. The neural net classification model was "trained" using 66 random observations from the database. The target variable in this case was whether the stock price increased or decreased after six months. This model correctly classified 100% of the observations. This model was then tested with the holdout group of 15 observations. The results are reported in Table 2.

	Classified Negative	Classified Positive	Total
Actual Negative	**2**	4	6
Actual Positive	3	**6**	9
Total	5	10	15
Sensitivity	40%	60%	

Table 2 – ANN Classification Performance

These results are similar to those gleaned using an ANN predictor model. Again there appears to be no coherent pattern between the predictor variables and the classification of winners and losers when the ANN was applied to a randomly selected holdout data set.

CONCLUSIONS

Earnings management continues to plague global financial markets. Increased vigilance through the use of technology like neural networks holds out much promise for helping detect the presence of excessive earnings management practices that, in turn, will enhance the credibility of financial markets. Ex-post detection of earning management behavior needs to come early since time is management's primary ally. Related studies (Kashefi, 2002; Palmon, 1997) have shown that the type of management approach to restructuring (e.g., proactive versus reactive) can have a modest impact on short-term stock performance. However, the event time frame in some of these studies is measured in days. Clearly, as the event time frame lengthens, the opportunity for additional externalities and their effects increase. This in turn clouds the ability to effectively measure the impact of earning management on stock price performance. One of the purposes of this paper was to explore the use of neural nets for this type of market analysis. Neural nets offer some distinct advantages over some of the more traditional data evaluation methods including ease of use and fewer restrictive assumptions. In a broader sense neural net technology can be used, in combination with tighter auditing practices, as a balanced approach for better controlling earnings management. Several potential extensions to the present analysis include varying the event horizon, comparing across international markets, incorporating more detailed industry classifications, characterizing proactive and reactive announcements and classifying auditing standards. The continued evolution of "smart" information technology machines like neural nets holds considerable promise for more insightful analysis into complex business issues like earnings management (Castelluccio, 2001).

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