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ABSTRACT

This paper demonstrates how neural networks may be successfully applied to the problem of security selection in the Australian Stockmarket. In practice, it is unrealistic for a trader to apply capital to all securities available in the market, and a selection technique must be employed to reduce the number of securities competing for capital. Selection techniques are generally based on either fundamental analysis procedures, or technical analysis procedures. This paper focuses on fundamental procedures, and implements a neural network which enhances the effectiveness of these procedures.

1. INTRODUCTION

Essentially, there are two models in common usage which forms the basis of most traders' decisions. These are Fundamental Analysis and Technical Analysis. Fundamental Analysis involves a detailed study of a company's financial position, and is often used to provide general support for price predictions over a long term. Typically, traders using this approach have long-term investment horizons, and access to the type of data published in most company's financial reports. Fundamental analysis provides mechanisms to scrutinize a company's financial health, often in the form of financial ratios. These ratios can be compared with other companies in similar environments. Technical Analysis provides a framework for studying investor behaviour, and generally focuses only on price and volume data. Typically, traders using this type of approach concern themselves chiefly with timing, and are generally unaware of a company's financial health. Traders using this approach have short term investment horizons, and access to only price and exchange data.

Regardless of the decision model in use, there are a variety of common issues. One important issue, the subject of this paper, is the issue of security selection. Essentially, there are a great many tradeable securities in the market, and a trader has a limited amount of capital. Common to all investors is the desire to maximize returns. Security selection is the process that a trader uses to determine which securities are likely to have the best chances of capital appreciation, and therefore, represent the best investments.

This paper focuses on the fundamental model, and investigates strategies which fundamental analysts use to make the selection process. It briefly describes the characteristics of these processes, their origins and credibility, and then moves on to the enhancement of these processes using artificial neural networks.

This paper will not focus specifically on fundamental investment procedures. Rather, it will analyze research related to using fundamental data for security selection, with the aim of determining key fundamental variables in use. It will review the literature to date, highlighting the fundamental variables believed to be important within the literature. The paper will then settle on two differing techniques, and implement both techniques as benchmarks. It will then develop neural network models from the combined fundamental variables involved, and assess their effectiveness as security selectors.

2. REVIEW OF LITERATURE

There is a long established tradition of attempting to use the financial ratios produced from fundamental analysis as predictors of a company's future share price (or price direction).

The process of using fundamental variables to make stock trading decisions begins with Benjamin Graham, as early as 1928. Publication of Grahams work dates back to his first book, Security Analysis, in 1934. This book is still in print, now in its 5th edition. Graham produced a number of books distilling investment wisdom, including the Intelligent Investor, initially published in 1949. This book made detailed comments on the building of portfolios and selecting stocks. This book was last published in 1973. Graham urged investors to pay attention to three fundamental variables, namely size of firm, capitalization, and price-earnings ratio. The book provided detailed information of how to select companies using these variables. Research by Oppenheimer and Schlarbaum [1], tested Grahams approach to determine its effectiveness. They extracted the rules provided to investors in each of the four editions of The Intelligent Investor, and using publically available information, found that positive risk-adjusted rates of return were delivered to investors that followed the approach between 1956 and 1975. Rates of return were 3% to 3.5% higher than a naïve buy-and-hold stategy (in a frictionless market). When the various market frictions (costs) were taken into account, rates of return were 2% to 2.5% higher than the buy-and-hold

strategy. Oppenheimer and Schlarbaum state that '...it is reasonable to conclude that our evidence contradicts the semi-strong form of the efficient market hypothesis'.

According to Lowe [2], Graham also published a list of ten attributes of an undervalued stock, which could be used by investors seeking excess return. These ten attributes were:

- Earnings-to-price yield double the AAA bond yield,
- P/E four-tenths highest average P/E in most recent 5 years
- Dividend yield two-thirds the AAA bond yield,
- Price two-thirds tangible book value per share
- Price two thirds net current asset value
- Total debt less than tangible book value
- Current ratio greater than or equal to 2
- Total debt less than or equal to net quick liquidation value
- Earnings doubled in most recent 10 years, and
- No more than two declines in earnings of 5 percent or more in the past 10 years

It was noted that few companies could meet all 10 criteria.

Grahams work inspired a number of researchers to focus on detecting security price return anomalies that could be ascribed to fundamental variables.

Basu [3] investigated whether stocks with low P/E ratios earned excess returns when compared to stocks with high P/E ratios. It was found that during the study period (April 1957 – March 1971), portfolios built from low P/E stocks earned higher returns than those portfolios built from higher P/E stocks, even after adjusting returns for risk. The study concluded that there is an information content present in publicly available P/E ratios, which could offer opportunities for investors, and that this was inconsistent with the semi-strong from of the EMH. There are some clear parallels with the first two guidelines of Graham's 10-point list here. The first guideline suggested earnings-to-price yield be double the AAA bond yield. The earnings-to-price yield is the inverse of the P/E ratio, and ensuring it is greater than the AAA bond yield effectively capped the P/E ratio. In this manner, it steered investors away from high P/E stocks. The second guideline required P/E be four-tenths highest average P/E in most recent 5 years, again, effectively steering the investor away from high P/E stocks.

In 1981, Banz [4] focused on the 'size effect'. Essentially, the size effect concerns the relationship between the market capitalization of a firm, and its return. Banz reports that during the study period (1936 – 1975), common stock of small firms had higher returns than the common stock of large firms, even after adjusting for risk. Banz also raises the issue that the size effect may just be a proxy for one or more other factors, which are correlated with size, an interpretation he also applies to Basu's findings concerning the P/E effect.

Also in 1981, Reinganum [5] described a misspecification of the simple one-period CAPM model,

namely, that data on firm size can be used to create portfolios that earn abnormal returns. From studying small firms listed on the New York and American Stock Exchanges, during the period from 1963 to 1977, Reinganum discovered average rates of return for small firms to be nearly 20% per year greater than those of large firms.

In 1984, Rosenberg et al. [6] presented two strategies aimed at exploiting fundamental information to increase returns. The first, the "book/price" strategy buys stocks with a high ratio of book value to market price, and sells stocks with the reverse. The second strategy, "specific return reversal" computes specific returns per stock, and relies on the observation that specific returns tend to reverse in the subsequent month. Thus, this strategy buys stocks with negative specific returns in the preceding month, exploiting this reversal. The study sourced data from Compustat, on 1400 of the largest companies, from 1980 to 1984, and stocks were priced mainly from the NYSE. The study demonstrated statistically significant results of abnormal performance for both strategies, and suggests that prices on the NYSE are inefficient. Here, the first strategy provides support for Graham's fourth guideline, namely that price be two-thirds tangible book value per share, effectively steering the investor toward stocks with a higher book value than price.

DeBondt and Thayler [7] present evidence that investors tend to overreact when considering recent data. This overreaction led to a reversal effect, with stocks that had been prior 'losers' likely to become future 'winners'. The researchers also investigate seasonality patterns in returns data. They demonstrate that the winner-loser effect is not primarily a size effect, and the earnings of 'winner' firms and 'loser' firms show reversal patterns consistent with overreaction. In terms of seasonal influence, DeBondt and Thayler report that excess returns for 'losers' are negatively related to both long-term and short-term formation performance, particularly in January. For 'winners', they find that January excess returns are negatively related to the excess returns for the prior December.

Detailed research from Fama and French [8] surveys the above style of anomaly detection, and conclude that if asset-pricing is rational, then size and the ratio of book value of a stock to its market value must be proxies for risk, as opposed to reflecting market inefficiency.

Lakonishok et al [9] find that a wide range of value strategies (based on sales growth, Book-to-market, Cash flow, earnings, etc) have produced higher returns, and refute Fama and French's claims that these value strategies are fundamentally riskier. Using data from end-April 1963 to end-April 1990, for the NYSE and AMEX, Lakonishok et al find evidence that the market appears to have consistently overestimated future growth rates for glamour stocks relative to value stocks, and that the reward for fundamental risk does not explain the 10% - 11% higher average returns on value stocks. This study lends further support to the fourth guideline, again effectively steering the investor toward stocks with a higher book value than price.

Fama and French [10] respond to Lakonishok et al by focusing on size and book-to-value, and form portfolios of stocks partitioned by these variables from the NYSE, AMEX and NASDAQ, from 1963 to 1992. Their results demonstrate that both size and BE/ME (book-to-market equity) are related to profitability, but find no evidence that returns respond to the book-to-market factor in earnings. They conclude that size and BE/ME are proxies for sensitivity to risk factors in returns. Their results also suggest that there is a size factor in fundamentals that might lead to a size-related factor in returns.

Later, Fama and French [11] study returns on market, value and growth portfolios for the US and twelve major EAFE countries (Europe, Australia, and the Far East). They recognize that value stocks tend to have higher returns than growth stocks, finding a difference between low B/M (Book-to-market) stocks and high B/M stocks of 7.68% per year on average. They find similar value premiums when investigating earnings/price, cash flow/price and dividend/price. They find that value stocks outperform growth stocks in twelve of thirteen major markets during 1975 – 1995. They also find a value premium in emerging markets. Fama and French conclude that these results are explained by a one-state-variable ICAPM (or a two-factor APT) that explains returns with the global market return and a risk factor for relative distress.

Frankel and Lee [12] estimate firms fundamental values (V) using I/B/E/S consensus forecasts and a residual income model. They find that V is highly correlated with stock price, and that the V/P ratio is a good predictor of long-term returns. They state that this effect is not explained by a firm's market beta, B/P ratio, or total market capitalization (size). They also find evidence that errors in consensus analysts forecasts are predictable, and these prediction errors can be exploited by incorporating the error with V/P. They conclude that the evidence suggests that firm's value estimates may well provide a better forecast ability than simply using ratios, and that prices converge to value estimates gradually over greater than 12 month horizons. They also state that the predictability of long-term forecast errors in consensus forecasts is consistent with a long-term mispricing hypothesis. Finally, the authors also acknowledge that the results may demonstrate yet another proxy for cross-sectional risk differences, but state that this is an unlikely conclusion.

Piotroski [13] investigates whether fundamental analysis can be used to provide abnormal returns, and right shift the returns spectrum earned by a value investor. In anomaly terms, Piotroski focused on high book-to-market securities, and shows that the mean return earned by a high book-to-market investor can be shifted to the right by at least 7.5% annually, and a simple investment strategy based on high book-to-market securities generates a 23% annual return between 1976 and 1996. The research is stimulated by the observation that portfolios of high book-to-market firms normally contain several strong performing firms (achieving strong returns), and many deteriorating ones (achieving poor returns). Piotroski defines three different classes of financial performance signals, namely:

- Profitability,
- Leverage, Liquidity and source of funds, and,
- Operating Efficiency.

From these three classes of signals, nine simple signals are defined, and an aggregate score of the nine signals is used to rank the constituents. The nine signals involve seven fundamental variables, namely:

- net income before extraordinary items,
- cash flow from operations, (both scaled by the beginning of year total assets),
- leverage,
- liquidity,
- whether external financing has been raised recently,
- current gross margin scaled by total sales, and
- current year asset turnover ratio.

Within the portfolios constructed from the higher aggregates, Piotroski notes that the returns are concentrated in small and medium sized companies, companies with low share turnover, and firms with low analyst following. It is also noted that superior performance is not dependant on initial low share prices. Again, support is found for Graham's fourth guideline in this study. Of further interest is the determination that one-sixth of the annual return difference between the ex-ante strong and weak firms is earned over the four three-day periods surrounding earning announcements. This information is of obvious interest to those advocating market timing approaches.

Kanas [14] finds a non-linear relation between stock returns and the fundamental variables of dividends and trading volume.

Aby et al. [15] focus on combining fundamental variables to screen stocks for value. This is a reasonably common approach, with some authors reporting outstanding results. Aby et al. developed portfolios based on four fundamental conditions, namely: Single Valued P/E (P/E<10), Market Price < Book Value, established track record of return on Shareholder Equity (ROE > 12%), and dividends paid out less than 25% of earnings. They conclude that when the four criteria are used to screen stocks, quality investments seem to result, again providing support for Graham's fourth guideline. The authors state that higher yields do not seem to provide good long term returns, possibly due to the use of retained earnings to enhance equity per share. Overall, the main contribution of their work is to establish a relationship between ROE (> 12), and share price performance. The research alludes to the fact that Buffett believes 12 is an appropriate value for ROE in (US) domestic markets. The authors find that the value of 12 for ROE provides a clear line of demarcation between performance and non-performance is share price terms. The authors tested the filter criteria against the Value Line database between August 31, 1989 to August 31, 1999. The filter conditions described cut the database down from 6000 possible stocks to just 14.

These 14 yielded an average return of 30.55% per year for the ten years. It is interesting to note that in earlier work [16], the same authors had focused on shares with simply a low P/E and a market price below book value, and had concluded that this filter method did not produce satisfactory returns.

3. METHODOLOGY

This paper will focus on the 10 stock selection rules ascribed to Graham, and the four stock selection criteria from Aby et al. Essentially the goal is to benchmark both of these selection criteria in the Australian market, and then to determine whether they can be improved upon using a neural network.

To measure the success of the selection criteria, and the neural networks, it is necessary to determine what the basic purpose of a selection mechanism is. Essentially, a trader must attempt to allocate capital to those securities that he feels have the most likely chance of a successful profit outcome. The results of this choice are easily measured using a simple metric, as follows:

$$FilterSelectivity = \frac{(ClosedTrades * 100)}{TotalTrades}$$

where

ClosedTrades is the number of trades closed due to meeting the predefined increase in value
TotalTrades is the total number of trades selected by the screening strategy

This paper uses 10 years of data for the entire Australian stockmarket from the first day of trading in 1994, through to the last day of trading in 2003. The data used includes delisted shares, so as to avoid survivorship bias in the results.

For the neural network part of the study, the data is divided 80:20, thus 80% of the data (the first 8 years) is used to predict known results for the last 20% (the last 2 years).

In this study, only ordinary shares are considered. Technical data (O/H/L/C/V) is acquired for each ordinary share, and this data is merged with fundamental data from the previous year. This merged data is displaced by 6 months, to avoid acting on data that was not available to the market at the time of use. This timeframe is consistent with previous studies, such as Halliwell et al. [17].

The neural network used in this study utilizes the backpropagation model and implements a logistical sigmoid function as the activation function. Inputs to the network are raw variables, rather than deltas. There is debate over whether raw variables or changes in variables are better as predictors. According to Azoff [18], the use of raw data is preferred to differences, to avoid destruction of fragile structure inherent only in the original time series. This was confirmed by Longo [19], who achieved significantly better results with neural networks using raw as opposed to transformed data.

Although this suggests that raw data values should be passed to the input nodes, it does not address the issue of range scaling. Typically, some form of normalization is needed, given the sensitivity of neural networks to outliers in the data. General approaches in the literature are to bound the range of input variables to within a number of standard deviations around the mean. As always with neural networks, determining the actual number of standard deviations that works best is a matter for experimentation.

There are no standard rules available for determining the appropriate number of hidden layers and hidden neurons per layer. General rules of thumb have been proposed by a number of researchers. For example, Shih [20] suggests constructing nets to have a pyramidical topology, which can be used to infer approximate numbers of hidden layers and hidden neurons. Azoff [18] quotes a theorem due to Komolgorov that suggests a network with one hidden layer and 2N + 1 hidden neurons is sufficient for N inputs. Azoff concludes that the optimum number of hidden neurons and hidden layers is highly problem dependant, and is a matter for experimentation.

An alternative approach described by Tan [21], is to start with a small number of hidden neurons and increase the number of hidden neurons gradually. Tan's procedure begins with 1 hidden layer, containing the square root of N hidden nodes, where N is the number of inputs. Training the network takes place until a pre-determined number of epochs have taken place without achieving a new low in the error function. At this point the network is tested against the in-sample set, and benchmarked. A new neural network is now created with the number of hidden nodes increased by 1, and the training and in-sample testing is repeated. After each test, the metric being used for benchmarking is assessed, to see if the new network configuration is superior. This process continues while the networks being produced are superior, that is, it terminates at the first network produced which shows inferior in-sample results.

To address the issues related to uncertainty of ANN configuration, Tan's approach will be used to determine the correct number of hidden neurons. Training will take place until 500 epochs have not produced a new error low. Each ANN architecture will be trained with unbounded input data, and then again with input data bounded to three standard deviations from the mean. In-sample results for the ASX Allshare will be presented for each configuration, and out-of-sample results will be presented for the best performing configuration.

The network was trained against the ASX Allshare to select a stock as either a 'winner' (output value 100), or a 'loser' (output value 0). A 'winner' is defined as any stock that appreciates in value more than 100% within 1 year. A 'loser' is everything that is not a 'winner'.

The ANNs contains 14 data inputs. These are the fundamental variables required to implement both the Graham screening strategy, and the Aby et al. strategy. The actual data items are:

- P/E Ratio
- Book Value per share
- ROE
- Payout Ratio
- Dividend Yield
- Price to Book ratio
- Total Current Assets
- Total Gross Debt
- Weighted Average Number of Shares
- Current Ratio
- Earnings per Share
- Year End Share Price
- ASX200 indicator
- AAA return proxy

The distribution of the data is shown below:

Variable	Mean	Stddev
DIVYLD	0.03	0.33
PRICE2BOOK	303.62	84,304.99
TOTALCURRENTASSETS	76,602,984.00	230,713,424.00
TOTALGROSSDEBT	80,401,776.00	267,895,360.00
WAVGSHARES	140,693,776.00	252,867,152.00
CR	7.53	29.69
EPS	9.62	131.74
PAYOUT	0.33	5.61
BVPERSHARE	1.40	12.77
ROE	318.89	22,842.05
PER	36.39	748.06

Table 1 Distribution of Fundamental Variables

Weighted Average Number of Shares, Year End Share Price, ASX200 indicator, and AAA return proxy were not adjusted. The final bounding applied to each of the variables in Table 1 is shown below in Table 2.

Variable	LOWBOUND	HIGHBOUND
DIVYLD	-0.96	1.02
PRICE2BOOK	-252,611.35	253,218.59
TOTALCURRENTASSETS	-615,537,288.00	768,743,256.00
TOTALGROSSDEBT	-723,284,304.00	884,087,856.00
WAVGSHARES	-1.00	899,295,232.00
CR	-81.54	96.60
EPS	-385.60	404.84
PAYOUT	-16.50	17.16
BVPERSHARE	-36.91	39.71
ROE	-68,207.26	68,845.04
PER	0.00	2,280.57

Table 2 Bounded Fundamental Data

4. RESULTS

A total of 1,222 securities (including delisted securities) had trading data during the test period, from which 22,944 input rows were used for training. These were selected by sampling the available datasets, and selecting every 50th row as an input row. Every 50th row roughly equates to every two months worth of trading data. The training range of the data is 8 years. Both of Grahams last 2 (of 10) points require 10 years worth of data to calculate. Hence, these two last points (selection rules) have been excluded from this study.

Each ANN has its output values scaled between 0 and 100. The trading strategies based on these ANNs establish positions when the output value exceeds 50. Basic benchmarks are provided to enable the reader to

assess the work in context. Table 3 shows these benchmarks. Included are the naïve strategy (buy-and-hold), the Graham strategy, the Aby et al. strategy, and a combined strategy, which consists of the union of the rules for the Graham and Aby strategies (consistent with the ANN combined approach).

	Closed Trades	Total Trades	Filter Selectivity
Buy-and-Hold Strategy	498	1222	40.7528642
Graham Strategy	0	0	-
Aby et al Strategy	52	127	40.9448819
Combined G & A	0	0	-

Table 3 Benchmark comparisons

Table 4 presents the results after determining the appropriate hidden number of neurons using Tan's approach.

Number of Hidden Nodes	Closed Trades	Total Trades	Filter Selectivity
4	1	1	100
5	2	4	50
6	3	5	60
7	7	10	70
8	0	0	-

Table 4 Hidden layer configurations tested

Table 5 shows the results of using the bounding process previously described to bound the range of each of the input variables. This process is used to attempt to make the ANNs more robust, and less susceptible to outliers in the data.

Number of Hidden Nodes	Closed Trades	Total Trades	Filter Selectivity
4	4	5	80
5	1	1	100
6	12	17	70.5882353
7	22	29	75.862069
8	2	3	66.6666667

Table 5 Bounded input data configurations tested

From Table 4 and Table 5, it is clear that the optimum configuration in both ANN construction architectures is using 7 hidden neurons. Table 6 presents out-of-sample results for the best configurations from Table 4 and Table 5.

Architecture	Opened Trades	Closed Trades	% in profit Open	% in profit Closed
Raw Data	3	2	0	100
Bounded 3 Stdevs	14	1	50	100

Table 6 Out-of-Sample Results

5. CONCLUSIONS

The results demonstrate that ANNs can be trained to identify stocks with a potential to rise significantly, on the basis of the stocks fundamental attributes. The ANN configurations in Table 4 and Table 5 each outperform their non-neural equivalents. The number of trades signalled appears low, however, on closer inspection, the arbitrary threshold of buying when the neural output

signal exceeds 50 is far too naïve. The value of 50 was chosen as it was half the range of the possible neural output signal. The majority of the trades generated at the signal threshold of 50 or more indeed continued on to achieve their 100% target, however, the price of many of them continued to fall significantly before the price rose and the 100% goal was achieved. During this time, the neural signal strength continued to increase.

Figure 1 below shows a breakdown of the output values of the best performing neural network[1] (scaled from 0 to 100) versus the average percentage returns for each network output value. The percentage returns are related to the number of days that the security is held, and these are shown as the lines on the graph. Put simply, this graph visualizes the returns expected from each output value of the network and shows how these returns per output value vary with respect to the holding period.
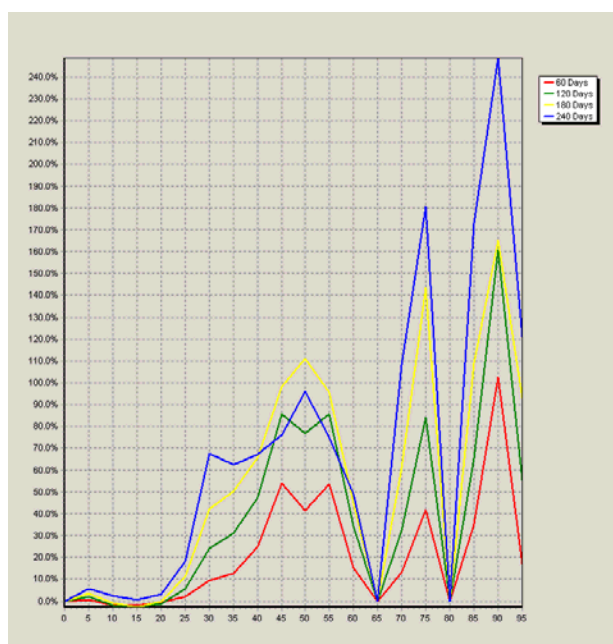

Figure 1 ANN output values

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[1] 7 Hidden Nodes, input data bounded at 3 standard deviations from the mean