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ENHANCING SECURITY SELECTION IN THE AUSTRALIAN STOCKMARKET USING FUNDAMENTAL ANALYSIS AND NEURAL NETWORKS

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Abstract

This paper examines financial trading from the aspect of security selection. In practice, it is unrealistic for a financial trader to participate in the full market of tradeable securities, and a selection mechanism must be employed to reduce the number of possible securities competing for investment capital. Essentially, there are two main methodologies used, namely, Fundamental Analysis, and Technical Analysis. This paper examines the practice of Fundamental Analysis, and demonstrates how neural networks can be practically employed to enhance the fundamentalist selection process.

Key Words

Neural Networks, Stockmarket Trading, Fundamental Analysis, Security Selection

1. Introduction

Fundamental Analysis provides a framework for modelling the financial mechanics of a company. Primarily, it aids in the formation of company or industry specific models, and provides a means of evaluating the performance of a given company in terms of those models. A significant contribution of the fundamental models is that they provide for the calculation of a number of financial ratios. These ratios are then used to assess the financial health of a company, and to compare directly to the ratios for different companies.

There is a long established tradition of attempting to use these fundamental ratios as predictors of a companies future share price. Primarily, this started with the work of Benjamin Graham in 1928, and forms the heart of an investment philosophy known as 'Value Investing'.

In direct contrast to the Efficient Market Hypothesis (EMH), value investors believe that the market does not price securities accurately, and that the true price of a security, its 'intrinsic' value, only rarely coincides with the market price. The trading manner of value investors is to determine the intrinsic value of a security, and acquire the security as long as the intrinsic value is above the price the market will sell at. Given time, value investors wait for the market to recognize the security was underpriced, and price it up accordingly. At this point, the value investor profits by selling the security.

It is widely believed that the structural determinants of market price change with time. Research cited below shows that whilst this is true, many of the fundamental characteristics of stocks reported decades earlier are still useful predictors of future stock prices today.

This paper will briefly review some of the primary fundamental characteristics used for security selection, and determine the place of artificial neural networks (ANNs) in increasing the efficiency of this process.

2. Review of Literature

2.1 Fundamental Analysis Literature

As mentioned earlier, the history of fundamental analysis as a trading mechanism began with Benjamin Graham in 1928. Graham published his first book, Security Analysis in 1934. This book defined the framework of Value Investment and is now in its fifth edition.

Since that time, a great deal of research focused on specific fundamental measures as key determinants of a securities future price. Basu [1] studied the relationship between P/E ratios and excess returns, and was the first to uncover evidence that appeared to oppose the EMH. Basu concluded that there was an information content present in publically available P/E ratios, and portfolios built from low P/E stocks earned excess returns even after adjusting for risk. In 1981, Banz [2] studied the size effect, and concluded that there was a relationship between market capitalization of a firm, and its returns, even after adjusting for risk. In 1981, Reinganum [3] confirmed that data on firm size could be used to create portfolios that earn excess returns.

Further fundamental anomalies were discovered, such as the book-to-market effect described by Rosenberg et al. [4], which found that stocks with a high book-to-market value yielded higher long-term returns. Fama and French [5] surveyed the above styles of anomaly detection, and concluded that if asset pricing is rational, then size and ratio of book to market value must be proxies for risk.

Lakonishok et al. [6] found a wide range of value strategies (based on sales growth, book-to-market, cash flow, earnings, etc) all produced higher returns, and refuted Fama and French's claims that these value strategies are fundamentally riskier. In 1995, Fama and French [7] responded to Lakonishok by stating that size and book-to-market equity 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 [8] studied returns on market, value and growth portfolios for the US and 12 major EAFE countries (Europe, Australia and the Far East). They found that value stocks tend to have higher returns than growth stocks, and conclude that these returns 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 [9] estimate firms fundamental values (V), using I/B/E/S concensus forecasts, and a residual income model. They find V is highly correlated with stock price, and that V/P is a good predictor of long term returns. Piotroski [10] focused on high book to market securities, and shows that the mean return earned by a high book-to-market investor can be right shifted by at least 7.5% annually. Piotroski also studied a number of different fundamental ratios and criteria with similar outcomes, and notes that returns are concentrated in small and medium size companies, companies with low share turnover, and firms with low analyst following.

Aby et al. [11] focus on using fundamentals to screen stocks for value. Aby et al. concentrated on four fundamental conditions, namely, single valued P/E's; Market price less than Book Value; established track record of return (established by ROE), and dividend payout ratio. The authors conclude that when the four criteria are used to screen stocks, quality investments seem to result. It is interesting to note that in earlier work [12], the authors had simply focused on shares with low P/E and a market price below book value, and concluded this filtering method did not produce satisfactory returns.

2.2 Soft Computing and Fundamental Analysis

The majority of soft computing techniques are data intensive, and rely on a large number of data points being available for training and testing. This is true of ANNs, and is the likely reason why very little work exists in the area of using ANNs in conjunction with fundamental analysis.

Falas [13] used ANNs to attempt to predict future earnings. Future earnings are widely thought to influence future security prices. Falas concluded that the ANN gave no significant benefit beyond the logit model, and suggested that the accounting variables chosen were not appropriate predictors.

Quah and Srinivasan [14] demonstrated the use of mainly fundamental variables to predict excess returns, however, their results demonstrated little except that their model bettered the SESALL index.

Longo [15] used ANNs to classify stocks into 'winner' and 'loser' categories using fundamental ratios and limited technical data, and demonstrated significant correlations between various fundamental data and excess returns.

As mentioned earlier, due to the large data requirements of soft computing, the vast majority of work in the soft computing arena is related to technical analysis, which is outside the scope of this paper. A detailed review of using soft computing techniques involving both Fundamental and Technical methods for trading can be found in the literature survey by Vanstone and Tan [16].

3. Methodology

This paper follows the work of Aby et al. [11], by introducing their screening mechanism into the Australian market, and using it as the basis for a neural network selector.

Essentially, the goal is to determine firstly whether the screening selection is suitable for the Australian market, and secondly, whether it can be improved upon by using ANNs.

To determine how to measure success in these goals, it is important to review the purpose of a selection model.

Specifically, a selection model is used to reduce (refine) the number of securities that are competing for capital, and, as a secondary consideration, to reduce the time taken for returns to be achieved. Thus, a suitable measure of success is to compare the percentage of stocks that achieve a pre-specified increase in value, and measure the average elapsed time to achieve that return. By measuring these values for the entire market, then for the results from the basic selection criteria, and finally for the ANN enhanced model, we can easily determine whether the strategy is effective.

The issue of risk is not addressed here. There are no uniformly agreed on procedures for beta estimation, and as investors are preoccupied with return, it is appropriate to consider risk appropriately controlled by trade risk (stop loss, money management, etc), not company risk.

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. The market is considered from the perspective of individual investors, as well as institutional investors. For this reason, results are presented for the entire ASX Allshare, and also presented for the S&P/ASX200. Individual investors have the opportunity to invest over the entire market, whilst typically, institutional investors invest in the S&P/ASX200 (the investable benchmark for Australia).

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 is NeuroLab (version 3). It utilizes a backpropogation 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 [15], who achieved significantly better results with neural networks using raw as opposed to transformed data.

The ANN contains 5 input variables, namely closing price, and the four fundamental variables used by Aby et al., namely PE Ratio, ROE, Dividend Payout Ratio and Book Value.

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'.

Primarily, to be valuable, a screening strategy must equal (or better) the entire market, measured in terms of the percentage of stocks selected that achieved the required return. Secondarily, the investor wishes to achieve this return within as short a timeframe as possible, and with a reduced subset of securities.

To restate the problem in terms of the objectives, the investor is seeking a stock selector which can provide the same level of opportunity for success (or better) as the entire market. Ideally, the subset of stocks selected should be smaller than the entire market, to allow the investor to allocate capital across the entire subset, thereby decreasing systemic risk through diversification.

As the selection process is a filtering process rather than a trading process, there is no need to take transaction costs into account. The study is not concerned with the amount of money that could have been made, rather, as in trading, this is seen as a function of money management, not security selection.

4. Results

4.1 Results for ASX (All shares)

Table 1-1 outlines the result of a naïve buy-and-hold strategy over the 10 year study period of the Australian market. Securities are purchased at the start of the study period (or as soon as available afterward), and held until they reached the 100% target, or the study period ended. The table describes the total number of stocks included, the percentage of stocks that achieved the 100% desired target, and the average time taken to achieve this result (in trading days). Results are presented inclusive and exclusive of delisted stocks, to enable the reader to assess firsthand the effect of survivorship bias on the selection strategy.

Timeframe	Includes Delisted?	Total Securities	Total Trades	Percentage achieving 100% return	Average trading days to reach 100% return
1994-2003	N	1315	1315	47.60%	693
1994-2003	Y	1557	1557	44.96%	693

Table 1-1 Naïve buy-and-hold, exit at 100% (Allshare)

Table 1-2 shows the result of running the basic filter described by Aby et al. against the ASX Allshare over the study period. The results are broken down into two timeframes, to enable easy comparison with the neural network model. These are the two timeframes used for the presentation of results. The strategy was to buy stocks as soon as indicated by the Aby et al. filter, and hold them until they appreciated by 100%. At this point they were immediately sold.

Timeframe	Includes Delisted?	Total Securities	Total Trades	Percentage achieving 100% return	Average trading days to reach 100% return
1994-2001	N	1222	125	41.60%	403
2002-2003	N	1282	59	38.98%	142
1994-2001	Y	1462	144	40.97%	392
2002-2003	Y	1365	64	35.94%	142

Table 1-2 Basic Fundamental filter (Allshare)

Table 1-3 shows the results of running the trained neural network against the ASX Allshare over the study period, broken down into in-sample, and out-of-sample timeframes. The in-sample training data for the neural network was the first 8 years of the data, and the out-of-sample data was the last 2 years.

Timeframe	Includes Delisted?	Total Securities	Total Trades	Percentage achieving 100% return	Average trading days to reach 100% return
1994-2001	N	1222	1034	54.16%	341
2002-2003	N	1282	903	46.62%	177
1994-2001	Y	1462	1125	53.42%	334
2002-2003	Y	1365	917	46.13%	177

Table 1-3 Trained Neural Network (Allshare)

Table 1-4 compares the results of the basic strategy with the results from the neural network. The neural network shows a significantly higher percentage of selected trades increasing by 100%. It also increased the amount of time taken to achieve this goal in out-of-sample testing, despite reducing it in in-sample testing. However, the goal that the neural network was trained for was to obtain superior selection ability. This neural network has achieved its primary function, of increasing the density of 'winner' stocks amongst the selected subset of stocks.

Timeframe	Includes Delisted?	% Increase in filtering efficiency	% decrease (increase) in time taken to achieve goal
1994 -2001	N	30.19%	15.38%
2002 -2003	N	19.59%	-24.65%
1994 -2001	Y	30.38%	14.79%
2002 -2003	Y	28.35%	-24.65%

Table 1-4 Comparison of Basic and Neural Results

4.1 Results for S&P/ASX200

Table 1-5 outlines the result of a naïve buy-and-hold strategy over the 10 year study period of the S&P/ASX200. This index was created in April 2000; for prior periods, a proxy was created that selected the largest 200 companies by market capitalization, and filtered them to ensure they traded on at least 80% of the trading days that data was available. This ensured a market was capable of being made in the security. Securities are purchased at the start of the study period (or as soon as available afterward), and held until they reached the 100% target, or the study period ended. The table describes the total number of stocks included, the percentage of stocks that achieved the 100% desired target, and the average time taken to achieve this result (in trading days). Results are presented inclusive and exclusive of delisted stocks, to enable the reader to assess firsthand the effect of survivorship bias on the selection strategy.

Timeframe	Includes Delisted?	Total Securities	Total Trades	Percentage achieving 100% return	Average trading days to reach 100% return
1994-2003	N	273	273	58.24%	889
1994-2003	Y	364	364	51.10%	870

Table 1-5 Naïve buy-and-hold, exit at 100% (S&P/ASX200)

Table 1-6 shows the result of running the basic filter described by Aby et al. against the S&P/ASX200 over the study period. The results are broken down into two timeframes, to enable easy comparison with the neural network model. These are the two timeframes used for the presentation of results. The strategy was to buy stocks as soon as indicated by the Aby et al. filter, and hold them until they appreciated by 100%. At this point they were immediately sold.

Timeframe	Includes Delisted?	Total Securities	Total Trades	Percentage achieving 100% return	Average trading days to reach 100% return
1994-2001	N	269	7	42.86%	483
2002-2003	N	269	3	33.33%	132
1994-2001	Y	360	8	37.50%	483
2002-2003	Y	294	5	20.00%	132

Table 1-6 Basic Fundamental filter (S&P/ASX200)

Table 1-7 shows the results of running the trained neural network against the S&P/ASX200 over the study period, broken down into in-sample, and out-of-sample timeframes. The in-sample training data for the neural network was the first 8 years of the data, and the out-of-sample data was the last 2 years.

Timeframe	Includes Delisted?	Total Securities	Total Trades	Percentage achieving 100% return	Average trading days to reach 100% return
1994-2001	N	269	13	61.54%	117
2002-2003	N	269	7	28.57%	208
1994-2001	Y	360	15	53.33%	117
2002-2003	Y	294	7	28.57%	208

Table 1-7 Trained Neural Network (S&P/ASX200)

Table 1-8 compares the results of the basic strategy with the results from the neural network. In considering the results for the S&P/ASX200, it is important to note that only a very small number of trades were taken. This has distorted the percentages. However, apart from 1 case, the neural network shows a significantly higher percentage of selected trades increasing by 100%. It also increased the amount of time taken to achieve this goal in out-of-sample testing, despite reducing it in in-sample testing. However, the goal that the neural network was trained for was to obtain superior selection ability. This neural network has achieved its primary function, of increasing the density of 'winner' stocks amongst the selected subset of stocks.

Timeframe	Includes Delisted?	% Increase in filtering efficiency	% decrease (increase) in time taken to achieve goal
1994 -2001	N	43.58%	75.77%
2002 -2003	N	-14.29%	-57.58%
1994 -2001	Y	42.21%	75.77%
2002 -2003	Y	42.85%	-57.58%

Table 1-8 Comparison of Basic and Neural Results

5. Conclusion

Figure 1-1 shows a breakdown of the output values of the neural network (scaled from 0 to 100) versus the average percentage returns (over the entire ASX Allshare holding period) 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.

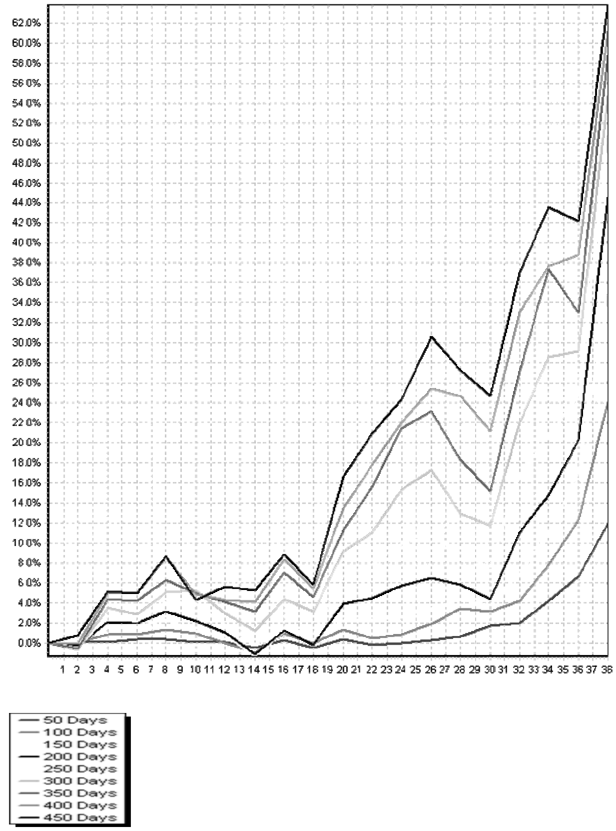

Figure 1-1 Average percentage returns for neural outputs

It is clear from this graph that increases in returns are due to a combination of the effectiveness of the neural network, and an increase in the holding period. It appears that the effect of these two variables works together, hand-in-hand. This graph shows that the neural network is indeed a potent selector of high-return stocks. However, one should be prepared to allow an extension of the holding period of these stocks to ensure maximum returns are obtained.

6. Future Work

There are a variety of other fundamental selection techniques available. It would be appropriate to study their effectiveness, and build a neural network selector from their combined input variables. This would allow a neural network to tune in to the appropriate variables for the Australian stockmarket.

The neural network used in this paper was trained only against the ASX Allshare. As such, it did not have the opportunity to determine different characteristics which may be present in the S&P/ASX200, as opposed to those characteristics of the ASX Allshare. It would also be appropriate to train the network against the S&P/ASX200 data to allow this learning opportunity.

Finally, this work needs to be put into a trading context. Specifically, a trading system consists of much more than simply the selection of stocks to trade. It involves money management, risk control and timing. It is appropriate to use a neural network such as the one created in this study as the first step in a complete trading model. It is in this direction that the authors own research is headed.

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