ANALYSING THE ASYMMETRIC INFORMATION ASSOCIATED WITH VALUE LINE TIMELINESS ONE RANKS

A DECISION RULE ANALYSIS

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The Efficient Market Hypothesis (EMH) assumes each security's price remains at continuous parity with its investment value. Accordingly, EMH denies that analytical trading rules using price or fundamental data result in strategies capable of outperforming market averages on a risk-adjusted basis after transaction costs. This paper demonstrates that analytical trading rules can outperform market averages. Specifically, the analysis shows the possibility of generating superior investment performance by selecting a population subset from the Value Line Timeliness Rank Ones. This study, utilising decision rule analysis, outperformed the Value Line Ones using a 90-day forecasting horizon on a risk-adjusted basis.

INTRODUCTION

There are many paradigms in finance. One is the contention that the stock market is efficient. The core concept is rather simple. In an efficient market any new information would be immediately and fully reflected in equity prices. Basically, stock prices appear to change randomly from one period to new and unanticipated information. Since this unanticipated information occurs randomly, stock prices at all times are efficient. Consequently, a financial market quickly, if not instantaneously, discounts all available information. Therefore, in an efficient market, investors should expect an asset price to reflect its true fundamental or intrinsic value at all times. This principle suggests, therefore, that neither technical analysis nor fundamental analysis can assist investors in identifying undervalued or overvalued stocks. This notion of market price randomness is similar to that association with encryption. A completely randomised encryption process should be immune from any sort of analytical attack. The only way to test for market efficiency, since the true fundamental value is unknown, is to detect whether some specific news is not yet fully incorporated in the asset price and could therefore be used to make some abnormal profit. As might be imagined the concept of an efficient market while still a significant paradigm in investment theory nevertheless continues to have its share of critics (Malkiel, 2003; Lo, 2000).

A number of classic factors have been used to detect the presence of market inefficiencies. These include 1) economic factors; 2) price momentum factors; 3) earnings momentum factors; 4) valuation factors; and 5) system factors. Tobin's Q, an example of an evaluation factor, provides a measure of the firm's future earnings potential. Entropy, a system variable, offers insights into the uncertainty associated with the future direction of the firm's stock price. The primary goal of this research was to assess the ability to detect market inefficiencies by combining both the technical and fundamental analysis of these four categories using powerful decision rule-based algorithms.

A two-stage analytical approach was used in analysing the Value Line Ones database. This investigation specifically focused on identifying variables from the categories listed above that might help explain future stock price movement. The first stage involved screening a large number of candidate explanatory variables using neural net analysis. Neural nets have been used extensively in the study of financial data (Wallace, 2008; Sexton, 2006). The target variable was the securities rank (0 or 1) based on the change in stock price over a subsequent 90-day period. Once a more manageable and parsimonious set of promising explanatory variables were identified, the second stage employed a classification and regression tree (CART) analysis to develop a set of investment decision rules. CART has seen widespread application in the analysis of financial data (Rachlin, 2007). Specifically, unlike other data mining techniques CART provides a set of operational decision rules. The investor can use these rules in making buy and sell decisions. This paper is organised as follows: 1) a review of the relevant literature and a brief overview on EMH; 2) an introduction to decision rule analysis; 3) a decision rule analysis of data derived from the Value Line Timeliness Ones; and 4) a discussion for using the modeling approach to make investment decisions.

LITERATURE REVIEW & BACKGROUND

A fundamental securities question is how effectively investor's expectations are incorporated into stock pricing. This is the concept of market efficiency. In an efficient market, the current prices of securities represent unbiased estimates of their true or fair market value. If all securities are correctly valued (by whatever method), investors will earn an expected return on their investment which is equal to the required return assumed by Capital Market Theory. Thus, in a perfectly efficient market in equilibrium, all securities are correctly priced. Hence, there are no under or over-valued securities. The existing price for the security is its correct price. The degree to which the markets are efficient has a profound implication for investors. If the markets are efficient then, all the time, money, effort, required knowledge, and anxiety of security analysis becomes meaningless. The central theorem is that the security market participants are competent and well-informed. Therefore, it is the competition between these very astute market participants that results in security prices being fairly and correctly priced. These market participants immediately 'compete away' any chance of earning an abnormal profit. Moreover, even if markets are less than fully efficient, indexing is more likely to produce higher risk-adjusted rates of return than active portfolio management after transaction costs (Malikiel, 2005).

The framework for this discussion is generally centered around Eugene Fama's seminal paper (Fama, 1970). This theory is more commonly referred to as the Efficient Market Hypothesis or EMH.

> *Fama defined efficient markets in terms of a 'fair game' where security prices 'fully reflect' all the information available. Consequently, if the markets are efficient, individuals can not consistently receive abnormal risk-adjusted returns. Utilizing the framework of the Capital Asset Pricing Model, this implies that the expected value of alpha for a diversified portfolio must be zero. This suggests that the complete measurement of risk can be noted in the beta. Hence, the market is efficient (securities are correctly priced) due to the absence of any excess alpha (positive or negative).*

Fama suggested that the Efficient Market Hypothesis (EMH) can be divided into the following three categories.

1. **Weak-Form**: The type of information being considered is restricted exclusively to historical price data. Investors should not be able to consistently earn abnormal profits by simply observing the historical prices of securities.

2. **Semi-Strong Form**: Asserts that security prices rapidly and correctly adjust to the release of all publicly-available information. Current prices fully reflect both past price data as well as all fundamental data. Therefore investors cannot consistently earn abnormal returns by action on public information.

3. **Strong-Form**: Represents the most extreme case of market efficiency. Under the strong-form security, prices fully reflect all information (public and private) and thus investors will not be able to consistently earn abnormal profits under any circumstances.

However, there is a growing body of research that question the efficiency of EMH (Lee, C, 2010; Howden, 2009; Haugen, 1996). For example, Haugen argues that the EMH paradigm is at the extreme end of the spectrum. In fact, the market overreacts to past records of success and failure with resulting incorrect or imprecise security prices. Furthermore, Grossman argues that it is impossible for a market to be perfectly informationally efficient (Grossman, 1980). This is because information is costly and therefore, prices cannot perfectly reflect all information. This suggests that a sensible model of market equilibrium must leave some incentive for information gathering thereby noting the value of security analysis. Thus, there may exist small differentials that can be exploited. These anomalies therefore are evidence of behavior that contradicts accepted theoretical prediction. Anomalies are statistically significant, risk-adjusted results net of transaction costs, which cannot be explained. A relatively recent alternative to EMH is the Adaptive Market Hypothesis (Lo, 2004). The core principles of the Adaptive Market Hypothesis (AMH) include:

- Profit opportunities will generally exist in financial markets
- Learning and competition forces will gradually erode these opportunities
- More complex strategies will persist longer than simple ones.

A recent study of AMH shows that technical trading rules can identify abnormal return opportunities although they tend to decline over time (Neely, 2009)

Selling short offers a complementary strategy for generating abnormal returns using analytically developed decision rules. A rational investor would like to sell short identified inferior stocks. Unfortunately, short selling has numerous problems. These challenges range from liquidity, inability to go naked, tick rules, flag rules, reporting rules, and ultimately a complete ban by regulatory agencies. Further, regulatory agencies can discriminate between individual investors and institutions. Nevertheless, recent data shows that short sellers increase their trading following positive returns, on days with significant buying pressure, and on days with high levels of asymmetric information (Diether, 2009). These patterns are robust in controlling for voluntary liquidity provision and for opportunistic risk-bearing by short sellers. The results are consistent with short sellers trading on short-term overreaction of stock prices. A trading strategy based on daily short-selling activity generated significant positive returns during the sample period. Additionally, it has been discovered that the volume of shorting demand activity is an important predictor of future stock returns (Cohen, 2007). An increase in shorting demand leads to negative abnormal returns of 2.98 percent in the following month. These outcomes are stronger in environments with less public information flow, suggesting that the shorting market is an important mechanism for private information revelation.

Implementing a combined trading strategy of going long stocks with recent high returns and going short with recent low returns can also generate abnormal large profits (Jegadeesh, 1993). When applied to the weak-form of the EMH, this is known as the price momentum anomaly. Semi-strong form EMH strategies such as going long, low price to book and selling short high, price to book have also received attention (Grinold, 2000). This study, using a minimum of 50 stocks to a portfolio, concluded that the benefits of long-short investing can have significant returns. This is particularly true when the universe of assets is large, asset volatility is low, and the strategy has high active risks. However, the long-short strategy is not a free lunch (Michaud, 1993). Typically, increases in active return are generally accompanied by increases in active risk. Furthermore, long-short investing might be most appropriate for special situations, niche investors, or for small portfolios. The portfolio constructed in the present study meets these two tests of (1) special situations or niche investors and (2) a small portfolio.

THE VALUE LINE TIMELINESS RANKING ANOMALY

One of the most consistent investment management anomalies is the Value Line Timeliness Ranks. The results from Value Line tend to refute the efficient market hypothesis. The methodology employed by Value Line ranks all stocks in its 1700 stock universe from one to five. The rankings are based on the expected price performance of the stocks for the next twelve months relative to the Value Line 1700 Index. There are one hundred ones; three hundred twos; nine hundred threes; three hundred fours; and one hundred fives which corresponds to a normal distribution. Value Line expects each rank to outperform the next lower rank. Table 1 provides a comparison on Value Line Timeless Rankings performance returns on a weekly and annual basis over the period April 15th, 1965 to December 31st, 2009. For example, the annual return for rank ones was 30,778 percent. The corresponding S&P 500 return over this same period on an annual basis was 1,165 percent.

Table 1: Comparison of Value Line Timeless Returns by Rank and Period (%)

Rank	Weekly	Yearly
1	15,575	30,778
2	10,727	4,174
3	4,924	252
4	2,846	-60
5	5,266	-99

Clearly revising the portfolio on an annual basis for the rank one stocks was the preferred strategy. The returns reported in Table 1 overstate actual performance since they do not transaction costs. Furthermore, investment management costs would be substantially higher when maintaining the ranks on a weekly basis which would further degrade the returns.

Many detailed studies have been conducted on evaluating the performance of Value Line (Zhang, 2010; Waggle, 2001; Choi, 2000; Copeland, 1982). The overall results suggested that the information in the Value Line's rankings would have been useful in generating larger than average returns. These studies do note, however, that due to transaction costs one may not have been able to actively trade these securities to benefit from what appears to be the Value Line's forecasting skill. But they further suggested that if one was buying securities, Value Line's ranking might help to differentiate among stocks that would do better in subsequent periods. The transaction costs associated with the entire portfolio may render any advantage meaningless. Transaction costs include commissions, bid-ask spreads, and slippage. The First Trust Value Line 100 Exchanged-Traded Fund (FVL) and the ProShares Value Line Timeliness Select Fund (PIV) provide two good examples of the problems associated with transaction costs. As the names imply, these funds actively select stocks from the Value Line One portfolio. These two funds therefore allow for an examination of the impact of transaction costs. Their real-time performances are important to the conclusions to this paper. The First Trust Value Fund (FVL) five-year performance as of 30 September 2011 for NAV was 5.25%. This should be compared to their benchmark, which is the Russell 3000 Index. This benchmark index showed a corresponding total return of (0.92 per cent). (This benchmark index can be actively utilised in portfolio management through the use of the Russell 3000 Index ETF (IWV); it had a five-year NAV performance of (1.02%) ending September 30, 2011.)[1] The five-year Sharpe Ratio of FVL was (0.11) vs. 0.00 for the benchmark for the five-year period ending October 31, 2011. The Alpha was a disappointing (2.42%) indicating inferior performance.[2] The ProShares Fund (PIV) is even more disappointing. The five-year NAV performance ending 30 September 2011 was (2.87%) vs. the noted benchmark at (0.92%). Further, ProShares dropped the Value Line Ones methodology as of 30 June 2010. The fund substituted the Standard and Poor's High Quality Ranking Index as their new target. This clearly showed the inability of ProShares to effectively use the Value Line Ones methodology in active portfolio management.[3]

MODEL VARIABLES

Selecting the right set of predictor variables is an essential ingredient for identifying abnormal return opportunities. Unfortunately or fortunately there are a large set of possible candidates. The computational dilemma when dealing with Ones Ranks on a quarterly basis is the small sample size (N = ~ 100). Therefore, the number of candidate variables must be selected with care. Even expanding the analysis to an annual basis yields a dataset of less than 400 observations.

Price Momentum, Earnings Momentum and Sales Momentum are three favourite candidates for predicting future share price values (Lee, 2009; Grinblatt,1995). The idea is that upward price, earnings, and sales momentum over the past six to 12 months is indicative of relatively strong performance in the next month. Similarly negative or sluggish momentum tends to predict poor performance. However, very few trends last forever. Hence, one observed weakness in relying exclusively on momentum factors is that they fade. For example, price momentum success could be the result of nothing more than investors chasing rainbows and willing to accept gambler's ruin. In general, the price momentum effect tends to be stronger and longer-lived than the earnings momentum effect (Chan, 1996). Standardise Unexpected Earnings (SUE) is another momentum factor that has received considerable attention (Latane, 1977). One form of SUE is defined as the actual earnings minus the standard estimate of earnings divided by the standard error calculated over twenty quarters. Thus, SUE measures the extent of the earnings surprise in terms of the number of standard deviations either above or below the forecasted estimate. The basic logic behind SUE is if there was a significant positive deviation the price of the security would drift upward during the coming period. The opposite would be true for the price of the security that had signally disappointed the trend.

Valuation is one of the more important aspects of active portfolio management. Active managers, in order to justify their roles and compensation, must believe that their assessment of value is better than the market or consensus assessment by providing a risk-adjusted return greater than a buy and hold strategy. The modern theory of valuation connects stock values to risk-adjusted expected total returns. This theory of valuation is closely related to the theory of option pricing and is consistent with Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). Further, valuation, or perhaps, more importantly mis-valuation, is clearly connected to expected returns.

The APT model assumes the importance of a firm's attributes and valuation fundamentals in its construction (Haven, 2007). In general, APT is an attempt to measure whether the stock is expensive compared to the current fundamentals. Valuation anomalies fall into the traditional empirical test of the semi-strong form of the Efficient Market Hypothesis. The valuation parameter of the price earnings multiplier is one example (Basu, 1997). Other candidates include PE normalised (PER), price to book (PBK) and price to intrinsic value (PVE).

ENTROPY

Entropy is a relatively new concept in finance. The concept of entropy was first applied to the study of thermodynamics in the late 1850s. In that context it was used to characterise the amount of energy in a system that was no longer available for doing work. Subsequently the definition has been expanded to a measure of randomness and disorder. In more modern times the theory of entropy has been extended to the study of financial markets (Pincus, 2008; Maasoumi, 2002; Molgedey, 2000). The basic idea is that more volatile securities have a greater entropy state than more stable securities. Two fundamentally different phenomena exist in which time-based securities data deviate from constancy:

- Exhibit larger standard deviations
- Appear highly irregular

These two phenomena are not mutually exclusive and as such both can be used to characterize the uncertainty associated with the fluctuations in security data. The standard deviation measures the extent of deviation from centrality while entropy provides a useful metric for delineating the extent of irregularity or complexity of the data set. Evaluating the subtle but complex shifts in series data is a primary prerequisite for exploiting the potential information contained therein. Pincus found, among other things, that approximate entropy (ApEn) is both robust to outliers and can be applied to times series with 50 observations or more with good reproducibility. A second measure of system complexity that is often used in this regard is called sample entropy (SaEn). The literature is replete with detailed discussions of these alternative measures of entropy (Thuraisingham, 2005; Richman, 2000). Both ApEn and SaEn were used in the presented study.

The basic ApEn and SaEn entropy models consist of three inputs:

- Time series
- Matching template length (M)
- Matching tolerance level (r)

For this study the time series length used was 50 months. The matching template length (M) used was two, which was predicated on the relative short length of the time series. The matching tolerance (r) was based on 20 per cent of the standard deviation. The 20 percent value for r has been used in a variety of serial studies (Abasolo, 2008;Liu, 2008). However, it has been suggested that the selection of the tolerance level (r) should be based on the value that maximises entropy (Lu, 2008). The computational process behind ApEn and SaEn is somewhat similar to the sign test. Smaller entropy values suggest that similar patterns will be followed by similar patterns (i.e. more structured data). If the time series is highly irregular then subsequent patterns will not mimic current patterns and the ApEn will be larger (i.e. greater serial randomness). This information should provide useful insights to future direction and behavior of the time series.

TOBIN'S Q

Tobin's Q is often used as an effective firm performance metric (Morgan, 2009; Fang, 2008). Tobin's Q is a forward-looking measure of a company's performance that represents investors' expectations about the risk-adjusted future cash flows of a firm (B. Lee, 2003). Because Tobin's Q is based on stock prices, it is less easily manipulated by managers compared to other performance measures (e.g. earnings). This study used the average value of Tobin's Q which compares a firm's market value with the replacement cost of its assets. The average Q is often used as a proxy for the more technically correct marginal Q. A simple estimate of Tobin's average Q is presented in the following (Chung, 1994):

$$Q = (MVE + PS + INV + DEBT)/ TA$$

Where:

- MVE equals the product of a firm's share price and the number of common stock shares outstanding
- PS equals the liquidating value of the firm's outstanding preferred stock
- INV equals the book value of the firm's inventories
- DEBT equals the value of the firm's short-term liabilities net of its short-tern assets, plus the book value of the firm's long term debt
- TA equals the book value of the total assets of the firm

A Q above one indicates that the market value of the firm's assets is greater than their replacement value, which suggests that the company should increase capital expenditures. In contrast a Q below one reveals that the firm's assets is less than their replacement costs which implies that the firm should consider acquisitions or selling assets rather than engaging in capital expenditures. The general goal, in either case, is to move Q towards one. In terms of using Q as a measure of corporate performance, a firm with an above average Q typically indicates excess profits which should provide a competitive advantage. Thus, a firm with a Q above one suggests superior growth opportunity compared with a Q below one, ceteris paribus.

The variables used in this study are listed in Table 2. The target variable, price change over the next quarter (PGQ), was converted to a binary format (1=TOP 50 VL stocks, 0 = Bottom 50 VL stocks, based on the quarterly percentage change).

Table 2: Candidate Variable Definitions

Variable	Definition
Beta	Adjusted Beta
CNE	Current to Normalized Earnings
EDV	Earning Variability
ROE	Return on Equity (%)
ROA	Return on Assets (%)
NPS	Net Profit Margin
CFL	Cash Flow Per Share
SED	Earnings Trend
PER	Price to Normalized Earnings
PEG	PE/Growth
PBK	Price to Book
PSS	Price to Sales
PVA	Price to Value
VMO	Value Momentum (%)
EMO	Earning Momentum (%)
SMO	Sales Momentum (%)
HEG	1Qt EPS growth
HEY	1Yr EPS growth
COM	Composite Price to Value
SDR	Relative Earnings Trend
OEY	Operating Earnings Yield
GRO	Projected growth rate
PVH	Price to value (5 year ave.)
HSQ	Sales growth (5-year)
HSY	Sales growth (1-year)
PEH	PE normal /5-year ave.
SUD	Standardized Unexpected Difference
SUE	Standardized Unexpected Earnings
QTY	Quality (1-8)
Q	Tobin's Q (ave.)
PRM	Price Momentum
AEV	Approximate Entropy
AEP	Approximate Entropy (%)
SEV	Sample Entropy
SEP	Sample Entropy (%)
PGQ	**Change in Quarterly Stock Price (%)**

DECISION RULE MODELS

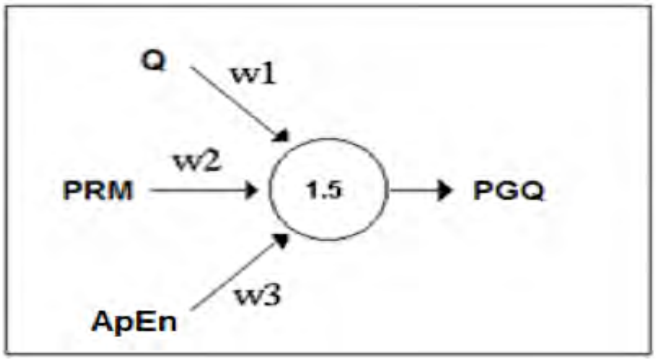
A number of decision rule analysis models have been used over the years in analysing stock performance. Two specific modeling approaches that have received considerable attention in this regard are neural nets and classification trees. This study employed the two models in a serial arrangement where the neural net pre-screened the candidate variable set and CART established the trading decision rules.

NEURAL NETS

Neural networks have been characterised as 'computing devices that use design principles similar to the information processing system of the human brain'. (Bharath,1994). NNs use complex network relationships to mimic the connections between sets of data. Among other things, NNs have the advantage of not requiring prior assumptions about the data or about possible relationships within the data, as is often the case with traditional analysis methods, for example, regression. In the most common schema, each neuron in one layer is connected to each neuron in the preceding layer as is illustrated in Figure 1. In this example, the classification of percentage change in quarterly stock price (PGQ) is derived as a function of input states and a set of weights. The specific input states in Figure 1 are the following: 1) Tobin's Q, 2) Price Momentum (PRM), and 3) Approximate Entropy (ApEn). The values for the input states may come from the activation of other neurons or specific environmental factors. 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 results in a PGQ classification change (i.e. 0 to 1). The values for the weights and thresholds are determined through an iterative process with the goal of minimising the aggregate error.

The architecture of an NN consists, at a minimum, of three layers: an input neuron or neuron layer, a 'hidden' layer and an output neuron. There may also be one or more intermediate or 'hidden' layers of neurons. Neural net models, like various regression techniques, are impacted by degrees of freedom. In some instances, adding more hidden layers can increase the degrees of freedom for a given database.

Figure 1: Example Predictive Neural Node



Specifically, NNs often appear as the analytical tool of choice when the underlying relationships between variables are somewhat ill-defined, as in the case of financial markets (Ilakaratne, 2009; Sen, 2004). Classification analysis is one of the most popular applications of NNs wherein the target variable is characterised into two or more categories. An example is credit screening prediction in which the target variable categories consist of approve, deny, or hold for further consideration (Ozkan-Gunay, 2007). The neural net model used in present analysis consisted of one input, one hidden and one output layer using Ward's Neuroshell classifier.

CLASSIFICATION AND REGRESSION TREES (CART)

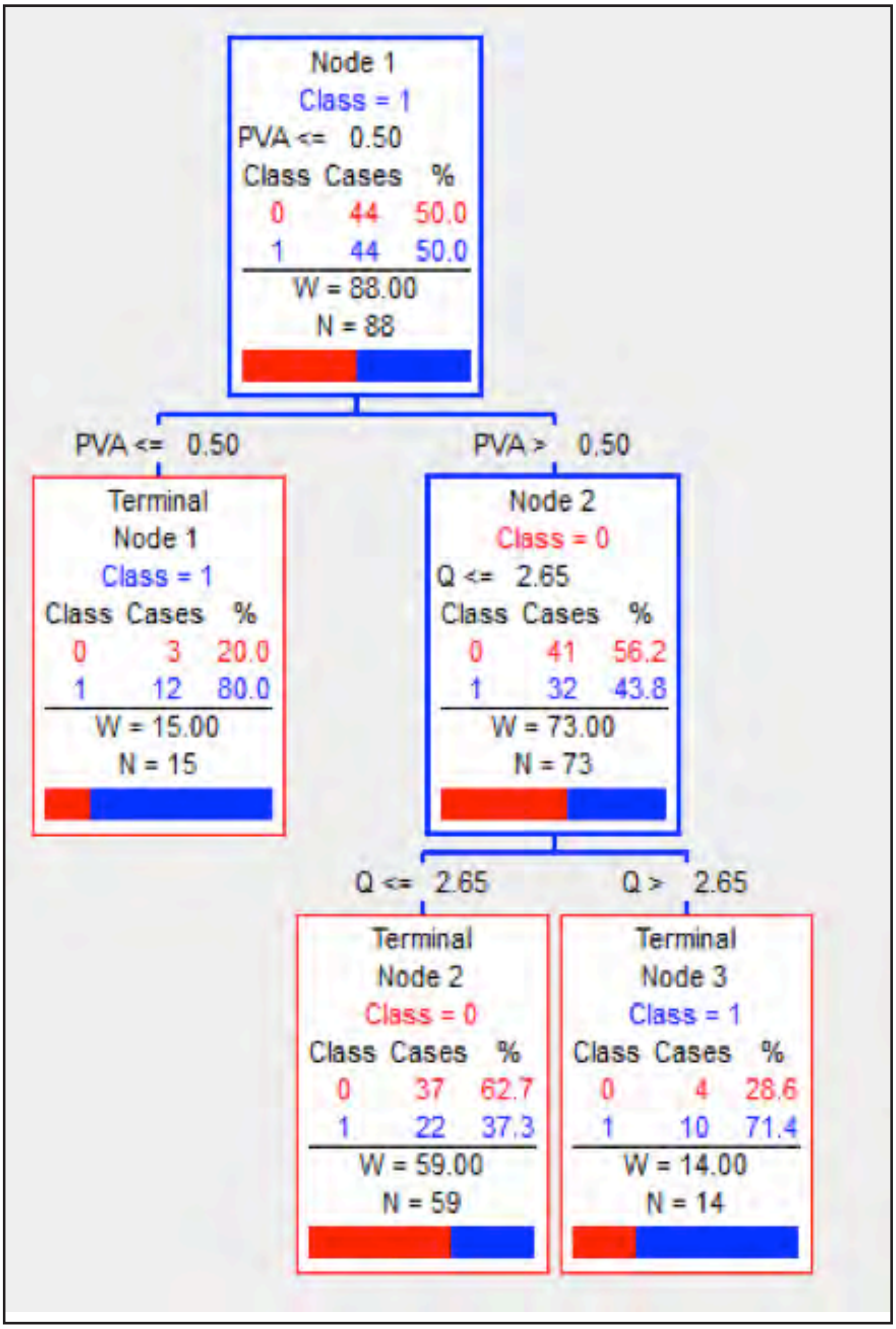
CART is a non-parametric analytical procedure that generates variable-based structural trees:

- Classification trees when the target variable is binary
- Regression trees when the target variable is continuous

Trees are formed by a collection of rules based on values of certain variables in the modeling process. Rules are selected on how well splits based on variables' values can differentiate observations of the dependent variable. Once a rule is selected and splits a node into two, the same logic is applied to each dependent node. The splitting process is terminated when no improvement in the model's performance can be achieved. Each branch of the tree ends in a terminal node. The data observations fall into exactly one terminal node. Each terminal node is uniquely defined by a set of rules. Figure 2 illustrates the tree splitting process for a small scale example. The first variable selected is price to value (PVA - node #1) which is split based on the rule of PVA < 0.50. Terminal node #1 shows a classification accuracy of

80 per cent. The variable selected next is Tobin's Q with a rule of Q < 2.65. The tree ends with terminal nodes #2 and #3. Typically, five to six variables are often needed to obtain the desired level of classification accuracy.

Figure 2: Example CART Structure



The CART modeling approach offers a number of advantages in many analytical situations (Su, 2010; Lewis, 2000).

- Results are more understandable compared with OLR and neural nets. Decision tree logic makes it easier to apply model outcomes

- Model is extremely robust to the effect of outliers. The data-splitting nature of decision rules makes it possible to distinguish between datasets with different characteristics and hence to neutralise outliers in separate nodes

- Relative ease in modeling variable interactions

CART has seen extensive application in the areas of commercial loan classification and financial distress (Bai, 2008; Kumar, 2008). In the Bai study, the CART model achieves better accuracy in identifying fraud cases and making predictions than the Logit regression model. Furthermore, the CART model with an industry benchmark performed slightly better than the CART without a benchmark. The Kumar study found that classification trees are more suitable than logistic regression for domestic credit scoring because of the characteristics associated with the sample data. Furthermore, it was observed that the use of the Logit model would have been precluded because of the large number of categorical variables and significant amount of missing data. One of CART's advantages is that it can handle missing data, contrasting relationships between variables in different parts of the measurement space, and outliers (Feldman 2005). This study was conducted without any pre-analysis that might have narrowed down the field of potential predictors. However, the pre-processing by another classifier can potentially improve the accuracy of the CART classifier (Abu-Hanna, 2003). This was the approach taken in the current study.

DATABASE

The database consisted of the variables identified in Table 2 from the end of fourth quarter 2008 (8-4) to the end of the first quarter 2010 (10-1). This timeframe embraced a total of six quarters. The data was gleaned from

1) Value Line Investment Survey, 2) Ford Equity Research Epic database, and 3) Mergent Online. The target variable was price growth quarterly (PGQ). This variable was lagged one quarter and was converted to a dummy variable (0 and 1) by evenly dividing the stocks based on rank order. Three different modeling time frames were used for estimating VL Ones quarterly performance based on technical and fundamentals data (i.e., one quarter, two quarters, and four quarters). The database was purged of extreme outliers (Hadi, 1994). Missing data was supplied using standard imputation procedures (Jerex, 2010; Walton, 2009). In a few cases company data was not available. Table 3 provides descriptive statistics for the six quarters database.

The variables with standard deviations larger than the means are shown in bold (e.g., EDV). An inspection of the max and min rows shows anomalous values for some of the variables. For example, the min value of -9.990 for CNE was set by the stop limits of the database and not by an actual calculation. An advantage of the CART model is its ability to handle outliers. However, for extreme cases, imputation procedures can be employed to develop a more realistic estimate based on the characteristics of other variables. In principle, this step should improve the classification accuracy of the model (Khamis, 2005). VMO averaged approximately 80 (out of a maximum of 100) which suggests that this metric provides less informational content compared to EMO and SMO. Tobin's Q averaged over twice the theoretical value indicating that Rank One firms offer the potential for superior growth. Entropy values based on 50 months

Table 3: Descriptive Statistics

Variable	Mean	S.D.	Max	Min
Beta	0.980	0.279	1.86	0.390
CNE	0.902	1.291	4.97	-9.990
EDV	98.773	304.371	3247	1.000
ROE	17.221	12.210	94.2	1.600
ROA	8.385	5.562	32.200	0.300
NPS	8.803	6.722	39.900	0.400
CFL	3.049	2.880	18.170	-11.250
SED	60.811	269.853	2811.000	-875.000
PER	29.089	30.026	368.800	4.800
PEG	1.938	1.481	14.750	0.480
PBK	4.521	6.319	89.780	0.740
PSS	2.438	2.311	17.600	0.070
PVA	1.041	0.860	6.570	0.260
VMO	80.453	16.188	100.000	20.000
EMO	64.091	21.270	100.000	6.000
SMO	64.869	23.208	100.000	4.000
HEG	13.851	30.457	98.529	-105.690
HEY	28.198	59.195	787.500	-250.438
COM	0.920	0.838	5.820	-4.330
SDR	0.338	1.074	5.410	-4.440
OEY	5.563	2.701	14.700	-13.500
GRO	14.767	4.563	25.000	5.000
PVH	0.943	0.647	8.650	0.090
HSQ	13.858	46.945	134.100	-58.500
HSY	12.314	26.019	444.800	-44.700
PEH	0.950	0.518	7.020	0.170
SUD	6.322	14.124	254.000	-13.400
SUE	2.990	3.324	28.300	-4.200
QTY	5.309	1.261	8.000	1.000
Q	2.290	1.490	8.343	0.185
PRM	54.105	97.732	958.700	68.000
AEV	0.526	0.115	0.842	0.117
AEP	0.451	0.129	0.901	-0.036
SEV	1.134	0.365	2.420	0.173
SEP	2.053	0.310	3.060	0.263

of data are reported for ApEn and SpEn both on a value and percentage change basis.

RESULTS ANALYSIS

As previously discussed the small sample size associated with the VL Ones suggest the need for a reduction in the original predictor variable set (Table 1). Furthermore, removing some predictors from consideration can improve a CART tree because those predictors can generate unfortunate splits which make it harder for CART to ultimately reach an efficient model. By eliminating some less auspicious splits from the CART, the end result is a better performing model overall. Accordingly, the neural net model was used to prune the original candidate list down to a more manageable and parsimonious subset. The results from the neural nets screening analysis of the 35 candidate variables is highlighted in Table 4. Each quarterly data set (with PGQ lagged one quarter) was processed using the neural net model. The relative influencing factors generated by the neural net were then used to rank the top ten variables on a one to 10 scale (e.g. PSS had the highest influence factor for quarter 8-4). The same procedure was used when quarterly data sets were combined (e.g., 8-4 and 9-1). Notice that both sample entropy (SEP) and Tobin's Q (Q) appear in most of the quarterly lists (bold).

Table 4: Short List Candidate Predictor Variable Set by Quarter

Rank	8-4	9-1	9-2	9-3	9-4	10-1
1	PSS	ROA	PSS	SMO	CNE	PRM
2	PRM	SUE	PVA	PSS	EMO	**Q**
3	PVA	PSS	***SEP***	ROA	SMO	ROA
4	ROA	SMO	PRM	EMO	VMO	VMO
5	***SEP***	EMO	SMO	***SEP***	PEG	EMO
6	VMO	***SEP***	**Q**	**Q**	**Q**	SMO
7	EMO	PRM	VMO	SUE	SUE	PSS
8	SUE	PVA	PEG	PRM	PRM	PER
9	PEG	PEG	EMO	PSS	PSS	***SEP***
10	SMO	VMO	ROA	***SEP***	***SEP***	COM

These pre-screened variable sets (Table 4) served as the basis for developing the initial investment rule sets using the CART methodology. As a general proposition evaluating the performance of analytical models should be based on out-of-sample data. Often complex models, like the ones used in this study, provide good with-in sample results but rather poor out-of-sample outcomes. This condition has to do with the so-called 'optimisation' principle — that is, a model based on with-in sample data tends to generate over optimistic performance (Picard, 1984). Accordingly, decision rules were developed for a given quarter and then applied to the next quarter (out-of-sample) where in both cases the target variable (PGQ) was lagged one quarter.

An example classification analysis is shown in Table 5 using the decision rules developed from quarter 9-4 and applied to quarter 10-1 data (i.e., holdout analysis, N=95). The CART generated decision rules correctly identified 66 percent of the winners (Sensitivity) and 69 percent of the losers (Specificity). The positive predictive value (PPV) and negative predictive value (NPV) were 0.67 and 0.67, respectively. For example, the reported PPV indicates that 67 percent of the winners that were classified as winners were classified correctly. The decision rule variables for the classifications given in Table 5 were PEG, SEP, SDR, Q, PSS, EMO and PSS. Interestingly, both the two "non-traditional" variables (entropy and Tobin's Q) were included in the optimised rule set.

Table 5: CART Classification Performance Example (Qt. 10-1)

	Actual			
Predicted	**1**	**0**		
1	31	15	67%	PPV[1]
0	16	33	67%	NPV2
Total	47	48		
	66%	69%		
	Sensitivity	**Specificity**		

[1] PPV = Ratio of the number of winners classified correctly divided by the total number of securities classified as winners.

[2] NPV = Ratio of the number of losers classified correctly divided by the total number of securities classified as losers.

A risk-return comparison was made between the performance of the VL Ones and the CART decision rules. Typically the metric of choice for this task is the Sharpe ratio (Maller, 2010). The classical definition of the Sharpe ratio is the rate of return for the portfolio minus the risk free return and dividing the results by the standard deviation of the selected portfolio. Thus the ratio provides a measure of the reward premium per unit of risk. A basic assumption is that the portfolio returns are normally distributed. When this is not the case or when there is excessive kurtosis the effectiveness of the ratio can be problematic. For this study the risk free return was dropped since the comparison between the Value Line Ones and the decision based rules is relative (Modified Sharpe Ratio).

Table 6 provides a performance comparison, based on the Modified Sharpe Ratio, for the Value Line Ones and the CART rules for several different database modeling timeframes (i.e., one, two and four quarters). The use of a multi-quarter database for developing decision rules for predicting subsequent quarter performance has some appeal. Among other things it lowers the cumulative annual transaction costs by reducing the frequency of trading. The optimised CART rules varied from case to case. The rule-based investment strategies were based on a minimum of at least 20 securities (Newbould, 1993).

Table 6: Comparison of Performance

Case	Qtrs/ Sample Size[2]	Quarter	Value Line Ones[1]	Going Long[1]	NSI[3]	Selling Short[1]	NSI[3]
1	1/89	9-2	0.289	0.392	38	0.210	53
2	1/91	9-3	0.775	0.853	51	-0.022	37
3	1/88	9-4	1.177	**0.771**	53	-0.043	40
4	1/93	10-1	0.513	0.553	38	0.485	56
5	1/94	10-2	-0.580	-0.328	46	-0.583	49
6	2/180	9-3	0.775	0.800	23	**0.789**	65
7	2/179	9-4	1.177	**0.598**	62	0.749	31
8	2/181	10-1	0.513	0.514	49	0.512	45
9	2/187	10-2	-0.580	-0.498	59	-0.728	36
10	4/361	10-1	0.513	0.613	49	0.418	45
11	4/366	10-2	-0.580	-0.493	70	-0.605	25

[1] Modified Sharpe Ratio

[2] Number of qtrs. and corresponding sample size in rule base

[3] Number of selected investments

The results depicted in Table 6 indicated that the CART models 'outperformed' the VL Ones based on the Modified Sharpe Ratio for the 'going long' strategy in all but two cases (highlighted in bold). These two cases embodied the same time period, namely quarter 9-4. This quarter was characterized by mainly positive gains (two thirds of the VL Ones). Furthermore, the losses for the 9-4 quarter were relatively small compared to the other periods that were analysed. The reported results of the long-position portfolio have significant pragmatic investment management implications. The only period in which the optimised CART long portfolio failed to outperform came in a period that could be considered 'an event' period. An event period cannot be anticipated or predicted. Therefore, excluding this event-type period, the optimised CART portfolio outperformed. A similar pattern was seen for the selling short strategy. This outcome is somewhat surprising since the Value Line Ones are geared towards upside performance. The selling short results can attest to the power of the CART modeling approach. Neither the Value Line Ones nor the CART estimates reported in Table 6 include transaction costs.

Conclusions

The purpose of this paper was to demonstrate that analytical based trading rules can outperform market averages over time. These trading rules were developed based on a two-step process using Neural Nets as a preliminary variable screening mechanism followed by CART for developing the actual trading rules. The results from applying the CART rules indicated superior performance compared to the Value Line Ones using the going long investment strategy. The situation for selling short is more problematical. This study introduced the use of two relatively underused predictor variables (Tobin's Q and Sample Entropy). Both factors were included in many of the final decision rule sets. The CART results show an overall improvement in performance as the training database is increased from one quarter to four quarters. Specifically, the 'selling short' strategy improved as the number of sample quarters was increased. The expansion of the number of quarters in the database used to generate the decision rules has the effect of reducing the annual transaction costs.

The overall results suggest that an analytical attack using both price and fundamental data can detect the presence of market inefficiencies. On an operational basis, the question is 'can there be enough of a differential that will allow an active portfolio manager to achieve above market risk-adjusted returns after transaction costs?' A potential further improvement to the modeling process would be to add a third category (2 = Winner, 1 = Neutral, 0 = Loser). This would have the effect of reducing the number of stocks included in the investment portfolio and in fine tuning the decision rule set for either going long or selling short. Another area for investigating would be to combine Tobin's Q and Sample Entropy into a mega variable (i.e. Q/SEP) for screening candidate winner and losers. Furthermore, including some economic factors like bond confidence, exchange rates and new housing starts might provide additional insights.

The Value Line Ones are positioned to advance relative to the market. Historical returns clearly support this fact. This paper has revealed that a competitive advantage can be gleaned by combining the Value Line Ones (known to outperform the market) with CART selections, which outperformed the Value Line Ones population. The active portfolio manager can now select stocks from a reduced list in designing a portfolio knowing that the resultant dossier will yield superior performance. Outside of perfect information of future returns, the use of CART selected stocks gives the active manager a competitive advantage.

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