Toward a Prediction Model of Position Outcome for Technical trading

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[Abstract] The objective of technical trading is to identify profitable conditions for the entry and exit of market positions. The future investment horizon is unknown at the beginning of a trade, but it is shorter than a traditional passive investment strategy. To trade technically is to predefine the conditions for both the entrance and exit of a market position. With predefined conditions that denote the beginning and end of a market position, the market for a security can be viewed as series of positions or "Events". Associated with a market Event is a set of market conditions that cause the equilibrium of a security's price to change. These market conditions can be quantified with the use of technical indicators that can be used as predictors of a market event outcome. In this paper we are using three common momentum indicators to classify the outcome (return) of a position defined by trading signals of a Simple Moving Average system. We are grouping the collection of positions associated with each selected security into outcome classifications in order to form an Analysis of Variance model. When the observed values of a momentum technical indicator vary with position outcome, it suggests that the indicator has a minimal level of predictive power that could be used for estimating the return of future positions defined by a Simple Moving Average trading system. The ensemble classification models will use a diverse set of technical indicators that measure various aspects of market sentiment at the time of entry signal as input features. This research intends to demonstrate that various ensemble classification models differ in their ability to classify the nonlinear relationships of market behavior and are anticipated to perform better than random chance. The outcome of this research may also provide indirect evidence that ensemble models can be applied to other markets such as commodities or more broadly to other complex non-linear problems.

[Keywords] Predictive modeling, technical analysis, technical trading, classification predictors, machine learning

Introduction

Technical Analysis is the systematic evaluation of past market data to estimate future price trends and make investment decisions (Kaufman, 2013, p.1). To trade technically is to predefine the conditions for both the entrance and exit of a market position. With predefined conditions that denote the beginning and end of a market position, it is argued that the historic pricing of a security traded with a technical system can be viewed as a collection of historic market positions. Associated with each market position is a set of market conditions that reflect the change in equilibrium of a security's price. It is suggested these market conditions can be quantified with the use of technical indicators and potentially used as predictors of market position outcome.

Speculative Investors react to market news and take positions in anticipation the security price will rise (or fall if short) in the near future. A short term investor will evaluate changes in the security's price in an effort to identify the change in the market equilibrium and the corresponding trend. The common objective of a speculator is to accurately anticipate the next move of the market. This can be accomplished by (1) recognizing recurring patterns in price movement and determining the most likely results of such patterns, and (2) identifying the "trend" of the market by isolating the basic direction of prices over a selected time interval (Kaufman, 2013, p.5). A unique aspect of this research is modeling a dynamic market "event" defined by a technical trading system opposed to forecasting future security pricing over some predetermined horizon (i.e. 1 day, 5days, etc.). It is argued that a target investment horizon of less than a quarter of a fiscal year focuses more on the market behavior of a security rather than traditional fundamental analysis. Modelling market events is more reflective of behavioral or how the market reacts to conditions. Using four randomly selected securities, this research paper investigates the relationship of three momentum based technical indicators to the outcome of market positions defined by a 21-day Simple Moving Average (SMA) trading system. The purpose of this research is to determine if technical momentum indicators vary with the classification of position outcome. The ultimate objective is to determine if the selected technical momentum indicators can be used as features in a prediction model to help form an expectation about position outcome at the time an entry signal is given.

Literature Review

Market Efficiency

The price of a security is determined by the market participants (buyers and sellers) of an open market. The theoretical equilibrium price of a stock is where the return on investment (appreciation of share value plus dividends) balances with the risk of the investment relative to the returns of a risk-free alternative (Kaufman, 2013, p.7). When the supply and demand dynamics of a security change the price must also change to bring the market back into equilibrium. More specifically, if the supply exceeds the demand, the security price should fall and if the demand exceeds the supply, the security price should rise (Tsai & Hsiao, 2010). Security prices will seek a level that balances the supply and demand factors. The equilibrium price point is reached either instantaneously or in an unpredictable manner as prices move in response to the latest available information or news release (Kaufman, 2013, p.6).

Market efficiency refers to the speed that information is reflected in security pricing (Gold, 1999). In a perfectly efficient market, new information concerning a security should be reflected instantaneously. However, if only some of the information is reflected in the security pricing instantaneously, and the remaining information takes a number of periods to be reflected (hours/days/weeks), then the market is less than fully efficient leading to short term mispricing and an opportunity to generate excess profit (CFA Institute, 2008). Markets cannot be fully efficient because of the costs associated with collecting and analyzing information, the cost of trading, and the limit of available capital to arbitrageurs (CFA Institute, 2008). As a result, security pricing generally reflects information up to the point where marginal benefits equal the marginal costs of information (Gold, 1999).

Behavioral Finance

There are several factors that influence stock prices including security performance, market trends, investor psychology, government influence, and changes in macroeconomic activity (Yoo, Kim, & Jan, 2005). Many professional investors argue that markets are dominated by the emotions of fear and greed which leads to investors addressing risky choices based on emotion instead of fact. Some investors are reluctant to realize losses, take profits too quickly, or suffer from other instances of irrational behavior which all can lead to mispricing in the market (CFA Institute, 2008). Most importantly, investors do not appear to be consistent in how they treat economically equivalent choices if the choices are presented in different contexts. Framing effects have been suggested to have an impact on rational decision making (Sharpe, Alexander, & Bailey, 1999, p.146). A number of researchers stated that stock prices are significantly correlated with the reaction to market event information (Yoo, Kim, & Jan, 2005). Market participants tend to overestimate the probability of unlikely events occurring and underestimate the probability of moderately likely events occurring, causing the tendency of investors to overreact to good and bad news (Bodie, Kane, & Marcus, 2003, p.178). This notion can be supported by the historic ‘rushes’, ‘booms’, ‘busts’, ‘bubbles’, and ‘market crises’ which provide creed to the notion that markets are less than perfectly efficient (Mangram, 2013).

Forecasting of Security Returns

There are several approaches described by various academics that attempt to predict future security prices. Traditional forecasting approaches include Auto Regressive Integrated Moving Averages (ARIMA) and Regression Analysis. An ARIMA model can be applied to predict future price movements in cases where financial time series data shows evidence of non-stationery. Regression Analysis can be used to model the relationship of market variables to security returns (Preethi, & Santhi, 2012). Fang and Xu investigated an approach that combines technical analysis and traditional time series forecasts. Their research suggested that technical trading rules and time series forecasts capture different aspects of market predictability (Fang, & Xu, 2003).

Although multivariate models have been widely used for predicting security pricing and stock market movements, several machine learning techniques are now becoming more common (Yoo, Kim, & Jan, 2005). Neural Networks (NN) have the ability to extract useful information from large sets of data (Preethi, & Santhi, 2012). Over the last decade, NNs have shown to better estimate future security returns over some traditional approaches, but have the tendency to over fit the data or find a local minima solution (Yoo, Kim, & Jan, 2005; Tsai, & Wang, 2009).Tsai & Wang proposed a stock price foresting model that combines a Neural Network and a Decision Tree to guard against over fitting (Tsai, & Wang, 2009). Weckman & Agarwala investigated the sensitivity of different technical indicators in an Artificial Neural Network (ANN) used to forecast n-periods into the future (Weckman, & Agarwala, 2003). Case Based Reasoning (CBR) can reuse past cases (or historic market positions) to estimate the outcome of new opportunities (Yoo, Kim, & Jan, 2005). Support Vector Machines (SVM) are based on statistical learning theory and are able to find a globally optimal solution (Yoo, Kim, & Jan, 2005). Leung et al. presented a structural support vector machine (SSVM) model with a complex graph input to represent relationships between various companies as factors that affect the stock price (Leung, MacKinnon, & Wang, 2014).

Both traditional multivariate models and machine learning techniques require a set of variables, commonly referred to as a feature set, that can be used as predictors of expected return over some future investment horizon. This research paper uses a 21-day Simple Moving Average trading system to define the entry and exit points of a position. The objective is not to forecast the security pricing n-periods into the future, but to estimate the return of a position defined by the Moving Average System which can vary dynamically in length. If the observed values of technical momentum indicators vary with historic position outcomes, then it may be possible to utilize technical momentum indicators as features within a classifier model to predict the outcome of future positions defined by a technical trading system.

Review of relevant Technical Analysis Indicators

Simple Moving Average (SMA). A trend is the general direction of the market or price of a security and can vary in length and intensity (Investopedia, 2014). A moving average can be used to smooth short-term fluctuations of security pricing and highlight longer-term trends or cycles (Preethi, & Santhi, 2012). During a period when the market of a security is trending, moving averages can be effective in timing position entry and exit signals (Kaufman, 2013, p.287). The Simple Moving Average (SMA) is defined as the mean of the most recent n-observations and can be calculated as followed:

$$SMA_t = \frac{P_{t-n+1}+P_{t-n+2}+\cdots+P_t}{n} = \frac{1}{n}\sum_{i=t-n+1}^{t} P_i, n \leq t$$

Accumulation/Distribution Oscillator. In 1972, Jim Waters and Larry Williams published a description the Accumulation/Distribution (A/D) Oscillator. The oscillator defined by Waters and Williams uses a unique form of relative strength to measure the implied direction of the day's trading (Kaufman, 2013, p. 397). The A/D Oscillator is calculated as followed:

$$ADO_t = \frac{(H_t-O_t)+(C_t-L_t)}{2\times(H_t-L_t)} \times 100$$

The maximum value of 100 is reached when a market opens(O) at the low(L) and closes(C) at the high(H). The Waters-Williams A/D Oscillator inherently adjusts to higher or lower trading ranges (volatility) as a result of the divisor being a multiple of the day's trading range (Kaufman, 2013, p.397).

Williams' %R. Williams' %R is a momentum indicator that measures overbought/oversold levels by showing the current closing price in relation to the highs and lows of the past n-observations (Achelis, 2001). The purpose of the indictor is to convey whether a stock or commodity is trading near the high or the low of its recent trading range. Williams' %R is different from stochastics as it measures the strength of the market close compared to the high of the past n-periods (Kaufman, 2013, p.401). As the close gets stronger the value of %R gets smaller. The William's %R indicator value can be calculated as followed:

$$\%R = \frac{\text{Buying Power}}{\text{Range}} = \frac{\max_{t-n}(\text{High}) - \text{Close}_t}{\max_{t-n}(\text{High}) - \max_{t-n}(\text{Low})} \times -100$$

Relative Strength Index (RSI). Developed by Welles Wilder, the Relative Strength Index (RSI) is a momentum oscillator that measures the velocity and magnitude of directional price movement. The RSI computes momentum as a ratio of higher closes to lower closes to measure the internal strength of a security (Achelis, 2001). The RSI is expressed as a value ranging from 0 to 100 and is calculated as follows:

$$\text{RSI} = 100 - \left(\frac{100}{1+\text{RS}}\right); \qquad \text{RS} = \left(\frac{\text{AU}}{\text{AD}}\right)$$

• AU = the average upward price movements during the past n-observations.
• AD = the average downward price movements (stated as a positive numbers) during the past n-observations.

Wilder suggested the significant threshold levels for the RSI indicator are 30 and 70 (Wilder, 1978, pp. 63-70). The center line for the Relative Strength Index is 50. If the relative strength index is below 50, the given security's losses are greater than the gains. When the relative strength index is above 50, the gains are greater than the losses over the previous n-observations.

Research Objective

The core focus of this research proposal is classifying the outcome of a dynamic market event opposed to forecasting the return of a fixed future time horizon (i.e. 1 day, 1 week, or 1 month). For the purposes of this research, the time between the entry and exit trading signals is referred to as an Event. The proposed research will investigate the use of ensemble classification models to predict the outcome of an event using technical market indicators as features.

The following figure illustrates the relationship between a security's time series and its event set

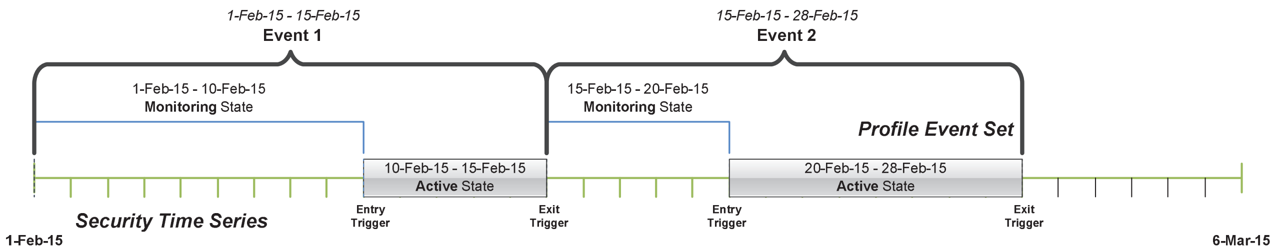

Figure 1. Illustration of events within a security time series

The performance of each classification model will be evaluated using the same set of events defined by the security and trading system combination.

Research Question

For the purposes of this research, a position is defined as the period between the entry and exit signals generated by a 21-day Simple Moving Average trading system. Although traditionally the response variable is the position outcome, this research is focused on the behavior of selected momentum indicators. Each of the three technical momentum indicators was considered for each position defined by the SMA trading system. The purpose of this paper is to investigate if the mean observed values of the chosen technical indicators vary with position outcome, where position outcomes are classified as Excellent, Favorable, Unfavorable, or Terrible. It was recognized that the technical momentum indicators may behave differently among securities, therefore, security was also considered as a factor.

Hypotheses

This research is designed around a difference question, specifically investigating if the observed technical momentum indictor, at the time of entry signal, varies among different position outcome classifications. This difference question is explored using a two-factor ANOVA ($\alpha = 0.05$). Each of the three selected technical indicators is evaluated independently. Correspondingly, the following sets of hypotheses are repeated for each of the selected indicators. So, if the mean observed value is statistically different among the outcome groupings and is independent of the security, then sufficient evidence exists to suggest that these indictors may have the potential to be a good predictor of the position outcome. For each of the selected indicators, we are investigating the following pairs of hypotheses:

1. ***H01***: μ Excellent = μ Favorable = μ Unfavorable = μ Terrible, there is no difference in the observed mean indicator value among varying position outcome classifications.

   Ha1: there is a difference in the observed mean indicator value among varying position outcomes.
2. ***H02***: μ NCI = μ NOG = μ PKT = μ SWS, there is no difference in the observed mean indicator value among different selected securities.

   Ha2: there is a difference in the observed mean indicator value among different selected securities.
3. ***H03***: The selected securities have no interaction with position outcome classification in terms of influencing the mean indicator observation value.

   Ha3: There is an interaction between position outcome classification and the different securities in terms of mean observed indictor value.

Data Collection

Trading Rules and Indicator Parameters

The Simple Moving Average indicator was used to form the technical trading system. The following rules were employed to denote the entry and exit points of a position. Only Long positions were considered.

Table 1
Position Entry and Exit Rules

Entry	*Exit*
Buy Long when the Closing price crosses above the moving average	Sell the long position when the Closing price crosses below the moving average

The timeframe parameter (n- observations/periods) was consistently set to 21 days for each of the indictors and the trading system (Simple Moving Average, Relative Strength Index, Williams %R). The value of 21 days represents a targeted trend of approximately three weeks and was chosen arbitrarily.

Securities and Data Used for the Analysis

This research uses four randomly selected securities from the S&P Small Cap 600 Index (Dowgett Investments, 2014). The four randomly selected securities are as follow:

Table 2
Selected Securities

Ticker Symbol	*Company Name*	*Industry*
NCI	Navigant Consulting Co.	Industrials
NOG	Northern Oil and Gas Inc.	Energy
PKT	Procera Networks, Inc.	Information Technology
SWS	SWS Group Inc.	Financials

For each of these selected securities, we collected data from Yahoo Finance through the period of January 1st 2009 to December 31st 2013.

MATLAB Simulation
A simulation tool was developed in MATLAB to support the research objectives. The simulation tool created a 'profile' for each of the selected securities. Within the profile, historic time series data was cross referenced with the 21-day Simple Moving Average trading system to generate a set of historic positions. Each selected security was simulated with End of Day data retrieved from Yahoo! Finance through the dates of January 1, 2009 – December 31, 2013. The number of positions for each security was dependent on the trading signals of the technical trading system. The calculations for each technical indicator were performed using the same historic time series data. The technical momentum indicator observation occurred at the time of a position entry signal.

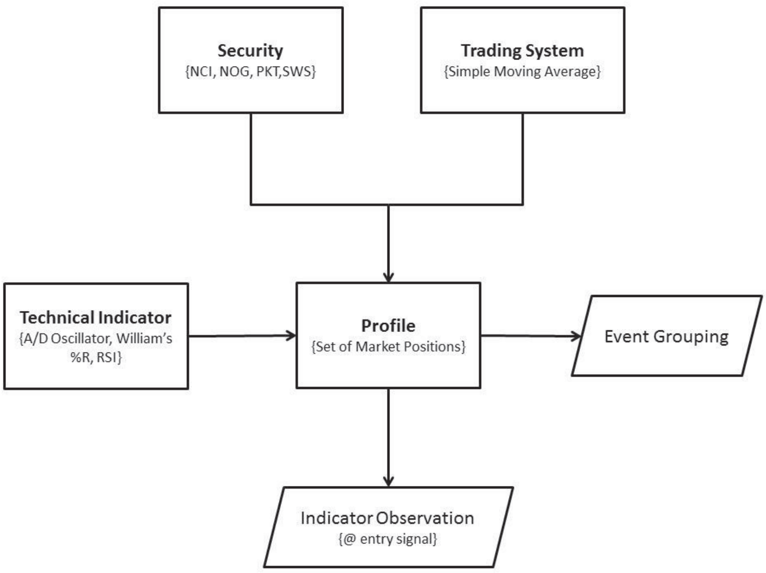

Figure 2. Conceptual outline of simulation tool

Table 2 presents an illustrative example for a position entry and exit. The position entry signal occurred on Feb 5th, 2009 and the exit signal occurred on Feb 18th, 2009. The observational values for the three selected technical momentum indicators were measured at the time of the entry signal.

Table 3
Example of a Position Defined and corresponding Technical Indictor observations

Date	Close$	SMA	Close - SMA	A/D Osc	Will %R	RSI
Feb 4	14.54	15.69	-1.15	37.2	-70.3	37.8
Feb 5	17.10	15.60	1.50	93.0	-28.91	44.7
Feb 6	17.55	15.57	1.98	76.5	-21.9	48.8
Feb 17	16.09	15.72	0.37	28.5	-41.3	50.2
Feb 18	15.71	15.74	-0.03	6.6	-47.6	51.6
Feb 19	14.94	15.85	-0.91	7.4	-66.4	57.0

Table 4 summarizes all of the identified historic positions of each selected security. The number of positions identified for each security varies. Note that the distributions of position outcome for each security have a large Kurtosis statistics and is slightly skewed.

Table 4
Historic Position Data, grouped by Security

Summary of All Position Outcomes (Returns as %)							
Sym	$\bar{X}$%	$\tilde{X}$%	*σ%*	*Kurt*	*Skew*	*Min%*	*Max%*
NCI	0.0	-1.3	5.7	6.0	1.9	-12.2	26.4
NOG	2.3	2.4	19.5	39.1	5.7	-22.4	142.0
PKT	0.8	-2.3	13.8	15.2	3.3	-23.0	80.6
SWS	-1.7	-2.3	5.1	23.8	4.1	-11.8	31.7

Analysis of Variance Experimental Design
The returns of the positions for each security were ranked and classified relatively into four equal quartile classifications. The top 25% of the greatest /best positions for a given security were classified as Excellent; the next 25% were classified as Favorable, and so on. The following table summarizes the position outcome classifications, by security, and the corresponding return statistics.

Table 5
Historic Position Data, grouped by Outcome

Summary of Positions, Grouped by Outcomes Classification								
	Excellent		**Favorable**		**Unfav.**		**Terrible**	
Sym	$\bar{X}$%	*σ%*	$\bar{X}$%	*σ%*	$\bar{X}$%	*σ%*	$\bar{X}$%	*σ%*
NCI	7.6	6.0	-0.8	0.3	-2.0	0.56	-5.0	2.2
NOG	21.4	31.7	-1.2	0.8	-3.4	0.5	-7.2	4.3
PKT	16.9	19.2	-1.2	0.8	-3.5	0.6	-8.4	4.5
SWS	3.3	7.6	-1.5	0.4	-3.0	0.5	-5.5	1.9
	11.5	**19.6**	**-1.2**	**0.6**	**-3.0**	**0.8**	**-6.4**	**3.6**

The two factors within the ANOVA experiment are position outcome classification and security. The response variable is the observed technical indictor value. Each technical indicator is analyzed separately. The following is a table with the number of observations considered per combination, per technical indictor.

Table 6
Sample Group Sizes of ANOVA Experiment

		Position Outcome				
		Exc.	*Fav.*	*Unfav.*	*Terr.*	***Total***
Security	*NCI*	19	18	19	19	**75**
	NOG	17	17	18	17	**69**
	PKT	19	19	19	20	**77**
	SWS	24	24	25	24	**97**
Total		79	78	81	80	318

Results

Accumulation/Distribution Oscillator

Table 7
A/D Oscillator Means Values, group by Outcome

	A/D Oscillator Mean Observational Value							
	Excellent		*Favorable*		*Unfav.*		*Terrible*	
Sym	$\bar{X}$	σ	$\bar{X}$	σ	$\bar{X}$	σ	$\bar{X}$	σ
Ave	*78.0*	*14.7*	*74.4*	*15.0*	*77.5*	*13.6*	*81.7*	*11.9*
NCI	80.1	9.9	70.2	14.7	73.7	16.8	81.7	10.0
NOG	79.3	16.0	77.6	10.7	75.4	12.0	79.0	14.9
PKT	77.6	13.9	71.4	19.8	79.9	14.4	80.1	12.6
SWS	74.9	18.8	78.2	14.8	81.1	11.1	85.9	9.9

Table 8
A/D Oscillator ANOVA Table

Accumulation/Distribution (A/D) Oscillator ANOVA Table					
Source	*Sum of Squares*	*Degrees of Freedom*	*Mean Squares*	*F Statistics*	*Prob. > F*
Security	629.5	3	209.832	1	0.3918
Position Outcome	2099.9	3	699.98	3.35	0.0195
Security* Position Outcome	2078.4	9	230.928	1.1	0.3597
Error	63180.9	302	209.208		
Total	68088	317			

Williams' %R

Table 9
Williams' %R Means Values, group by Outcome (The means have been multiplied by -1 in this table)

	Williams' %R Mean Observational Value							
	Excellent		*Favorable*		*Unfav.*		*Terrible*	
Sym	$\bar{X}$	σ	$\bar{X}$	σ	$\bar{X}$	σ	$\bar{X}$	σ
Ave	*40.4*	*13.0*	*43.9*	*9.5*	*42.2*	*10.6*	*36.9*	*14.4*
NCI	37.1	12.1	39.5	10.6	44.1	7.6	37.3	14.0
NOG	37.5	10.1	48.6	8.4	42.9	10.3	39.4	8.2
PKT	44.4	17.5	48.8	7.2	40.3	11.4	38.1	18.7
SWS	42.8	12.5	38.7	11.9	41.5	13.3	32.7	16.7

Table 10
Williams' %R ANOVA Table

Williams' %R ANOVA Table					
Source	*Sum of Squares*	*Degrees of Freedom*	*Mean Squares*	*F Statistics*	*Prob. > F*
Security	918.8	3	306.281	1.85	0.1387
Position Outcome	2118.8	3	706.264	3.35	0.0058
Security* Position Outcome	2430.6	9	270.064	1.63	0.1064
Error	50087.1	302	165.851		
Total	55572.6	317			

Relative Strength Index

Table 11
RSI Means Values, Group by Outcome

	RSI Mean Observational Value							
	Excellent		*Favorable*		*Unfav.*		*Terrible*	
Sym	$\bar{X}$	σ	$\bar{X}$	σ	$\bar{X}$	σ	$\bar{X}$	σ
Ave	*49.4*	*6.7*	*50.4*	*7.0*	*50.7*	*6.6*	*50.6*	*6.8*
NCI	49.1	6.5	52.0	7.8	52.1	7.9	51.6	6.8
NOG	50.3	6.6	49.8	6.8	49.5	6.3	49.9	6.1
PKT	48.7	7.4	49.1	6.7	49.4	5.8	49.7	8.3
SWS	49.7	6.4	50.5	6.5	51.9	6.4	51.2	5.9

Table 12
RSI ANOVA Table

Relative Strength Index (RSI) ANOVA Table					
Source	*Sum of Squares*	*Degrees of Freedom*	*Mean Squares*	*F Statistics*	*Prob. > F*
Security	185.53	3	61.8423	1.28	0.2811
Position Outcome	80.44	3	26.8134	0.56	0.645
Security*Position Outcome	102.26	9	11.3618	0.24	0.9892
Error	14584.98	302	48.2946		
Total	14964.97	317			

Interpretation of Results

The maximum value of the Accumulation/Distribution (A/D) Oscillator is reached when the market opens at the Low and closes at the High. Larger A/D Oscillator observations suggest greater market sentiment towards an upward price movement. The distribution of the observed values is skewed towards the higher end of the scale. This was expected as observations were recorded at the time of a Long entry signal from the 21-day moving average trading system. The Simple Moving Average trading system generates an entry signal when the close crosses the 21-day average. For the close to cross the average, the security pricing needs to advance upward pass the average value. The A/D Oscillator only takes into consideration the high, low, open, and close price points of the given period/day rather than taking into account a series of periods (n-observations). This led to significant volatility among the A/D Oscillator observations. Although the F statistic of the ANOVA experiment suggested that position outcome varied among outcome classifications, the distributions of observations among the outcome classifications challenged the assumptions of ANOVA. Correspondingly, the hypotheses associated with the A/D Oscillator are neither confirmed nor rejected.

The Williams %R indicator observations are measured on a negative scale ranging from −100 (lowest) up to 0 (highest). An observational value of −100 occurs when the close is at the lowest low of the past n-observations/days, and an observational value of zero occurs when the close is at the highest high of the past n-observations/days. Similar to the A/D Oscillator, the distribution of observed Williams' %R values are skewed towards the higher end of the scale, suggesting the indicator correctly identifies upward price movements. Similar to the A/D Oscillator, the F statistic of the ANOVA experiment suggests position outcome influences the value of the William's %R indictor as hypothesized although the assumptions of ANOVA were challenged. The hypotheses associated with the William's %R indictor are neither confirmed nor rejected.

The Relative Strength Index measures momentum by oscillating between 0 and 100 with an observational value of 50 representing market neutral momentum. Wilder suggested the n-observations parameter be set at 14 periods opposed to the 21 periods selected for this experiment (Wilder, 1978, pp. 63-70). The mean observed value was approximately 50 among all outcome classifications which suggested the RSI indictor provides little value for predicting future position outcomes. The F-statistic rejected the hypothesis that a difference in the mean observed value exists among the varying position outcomes. The observations of the Relative Strength Index indictor were approximately normally distributed and in line with assumptions of an ANOVA experiment.

There was no indication the selected indictors perform differently among the randomly selected securities. Furthermore, there was no indication of interaction between the selected securities and the outcome classifications among the selected indicators. The methodology used to assign the outcome classification label could be a possible explanation for these findings. Although the distributions of position returns varied among the different randomly selected securities, the relative ranking of the positions and corresponding assignment of position outcome label was performed within each security rather than among all securities.

As the number of positions for a given security were defined by the 21-day simple moving average trading system, it was not possible to guarantee the sample sizes were equal. For each security, the total number of positions was divided into even quartile classification groupings which ensured an equal number positions allocated to each outcome classification (+/- 1 observation), but not necessarily the same number of positions identified by the trading system among the randomly selected securities. If the sample sizes were equal, the assumption of normally distributed sample groups could be relaxed. Unfortunately, the variances of the observed indicator values (the response variable) were not consistent among each experiment groupings which made it difficult to draw definitive conclusions.

Future Research

It would be worthwhile to investigate clustering position outcomes rather than simply dividing the samples positions into four equally weighted classifications based on percentile. Given the distribution properties highlighted in Table 4, a clustering approach would likely result in a small number of extreme positions being assigned "Excellent" and "Terrible" classifications, and the majority of the position outcomes being assigned to the "Favorable" and "Unfavorable" classifications. Correspondingly, the research hypotheses could be reformed to investigate if technical indicators have the ability to discover outlier market positions, namely those in "Excellent" and "Terrible" classifications. Using all 318 positions from the four selected securities defined by the Simple Moving Average system in this experiment, the following table contains the top 10 positions with the greatest z-score, where the z-score is defined as $z = \frac{x_i - \mu}{\sigma}$. The z-score for each of the corresponding technical momentum indicator observations is also calculated and presented. It is interesting to observe that extreme position outcomes frequently have a corresponding extreme indictor observational value as defined by the z-score.

Table 13
Top Ten Position Outcomes by Z-Scores and Corresponding Indictor Observations

Position Return	**Position Return z-Score**	*RSI z-Score*	*AD Osc z-Score*	*Will %R z-Score*	Sym
26.38%	**2.17**	*-0.57*	*0.54*	*-0.06*	NCI
142.0%	**11.77**	*-0.46*	*0.74*	*1.25*	NOG
27.0%	**2.22**	*0.82*	*0.89*	*1.40*	NOG
35.4%	**2.92**	*-0.37*	*-0.25*	*0.43*	NOG
26.9%	**2.22**	*2.09*	*0.94*	*1.23*	NOG
40.32%	**3.33**	*0.45*	*-0.78*	*-1.15*	PKT
27.91%	**2.30**	*-0.92*	*-0.21*	*-1.96*	PKT
38.46%	**3.18**	*0.16*	*1.50*	*3.07*	PKT
80.57%	**6.67**	*1.59*	*0.65*	*2.09*	PKT
31.69%	**2.61**	*-1.50*	*-1.35*	*-0.87*	SWS

In addition to refining how positions are group into outcome classifications, it may be interesting to vary the targeted trends (number of n-observations) for the selected technical indicators as well as the parameters of the Simple Moving Average trading system. This research set the n- observation parameter consistently to 21 days for the Simple Moving Average, Relative Strength Index, and Williams %R indicator calculations. By varying the n-observation parameter the technical indicators will become more or less sensitive to the market fluctuation depending on if n-observation is decreased or increased, respectively.

Lastly, it is suggested to explore combining complimentary indicators to further investigate the possibility of developing a classifier that could be used to predict position outcome. At the time of an entry signal, multiple technical indicators can be used to measure various aspects of market sentiment in addition to momentum which was the focus of this research. Other market sentiment aspects may include the strength of the trend, volatility of the security pricing, and trading volume. There are various types of indictors that could be used in combination as a feature set in a more complex model to estimate position outcome. The concept of complimentary indicators was explored by Galloppo who suggested the simultaneous use of Moving Averages and Oscillator indicators leads to improved forecast power as a result of their ability to catch complimentary information in past prices more effectively (Galloppo, 2009).

Conclusion

This paper highlighted the concept of using technical momentum indicators as predictors of position outcome defined by a technical trading system. This paper indirectly investigated and assessed the value of three momentum based indicators. The A/D Oscillator and the Williams' %R indicators offer some potential of predictive power to classify the outcome of a position defined by a 21-day SMA trading system, although no conclusions were able to be drawn as the assumptions of the ANOVA experiment could not be validated; nor were the results fully convincing. Results of the Relative Strength Index (RSI) suggest no predictive power to classify the outcome of a position defined by a 21-day SMA trading system. The validation of the proposed predictive model has two aspects: internal validation and external validation. The internal validation will be demonstrated using the degree of variance of classifier performance over a variety of randomly selected securities and technical trading systems. While the external validation can be shown by repeatedly drawing additional securities from the population of possible securities and creating new trading systems do determine if we can get the same outcomes in terms of ensemble classification performance.

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