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"For the things we have to learn before we can do them, we learn by doing them."

—Aristotle, The Nicomachean Ethics

IFTA Journal

About cover photo:
Sydney, Australia—Surfer riding incoming wave in the morning.
— Photograph by keiichihiki

IFTA 2017

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Letter From the Editor

By Aurélia Gerber, MBA, CFA

Dear IFTA Colleagues and Friends:

While technical analysis covers a broad range of theories and techniques, it can be difficult for traders and investors to discern those that are nice to know from those that can be shown to have real profit-making potential. The *IFTA Journal* theme, along with the conference, will focus on what works for successful traders. The theme of this year's 29th conference in Sydney is "From theory to profitability—achieving better returns through technical analysis".

Technical analysis is the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends. The three principal sources of information available to the technician include price, volume, and open interest. The premises of technical analysis remain the same, however—price discounts everything; price movements are not totally random, they move in trends; and history has a tendency to repeat itself. Since the principles of technical analysis are universal, it is easy to broaden the focus to all financial markets, fostering a common language for traders and investors.

"From theory to profitability—achieving better returns through technical analysis"

The *IFTA Journal* is—through its global distribution to professionals in the field within member societies from 27 countries—one of the most important forums for publishing leading work in technical analysis. This year, there is an emphasis on practical and demonstrable outcomes from tools, processes, and techniques used by successful traders and investors. The variety of content provides unique opportunities for readers to advance their knowledge and understanding of the practice of technical analysis.

The *IFTA Journal* is divided into four sections:

In the first section, we have published nine Master of Financial Technical Analysis (MFTA) research submissions. This body of work offers multiple fresh ways of looking at the behavior of markets and is testament to the high standing of the MFTA designation. One paper deals with a time-independent charting system; four papers review indicators, including the practicalities of the SCTR, the square of nine band, moving average, and momentum on RSI oscillator; three papers introduce filtering systems based on RSI, Kalman filter, and pattern recognition to improve the performance of the signals; and one paper is on trend definition based on Entropy of Market Profile.

The second section includes articles submitted by IFTA colleagues. One article was submitted by a Society of Technical Analysts (STA) on the analysis of simple momentum on moving averages to major equity markets, one article is by the Technical Securities Analysts Association San Francisco (TSAA-SF) on a latest prediction study using point and figure data of the Dow Jones Industrial Average, and one article is from Hong Kong on the profitability of Stochastic Oscillators (STC) in major stock market indices.

In the third section, as the 5th year, we are happy to publish a paper from another organisation, and with the permission of the National Association of Active Investment Managers (NAAIM), we have included a paper by Spencer Seggebruch, winner of the NAAIM Wagner Award 2016. We hope that you find this paper most interesting.

Finally, for our fourth section, we are also very thankful to have had the support of our book proposal reviewer, Regina Meani, on "The Art and Science of Technical Analysis," by Adam Grimes.

This year's *Journal* was produced by a returning team for IFTA. I would like to thank, Elaine Knuth, Jacinta Chan, and Regina Meani for their help in editing this *Journal*. Articles were peer-reviewed by Elaine Knuth and Rolf Wetzer.

We are also able to create this timely and unique *Journal* because of the intellect and generosity of time and materials from the authors. It was their tremendous spirit and endeavour that enabled us to achieve the goals of this high-quality publication. We are indebted to all authors for their contributions and for enabling us to meet our *Journal* submission deadline.

Last, but not least, we would like to thank the production team at Management Solutions Plus—in particular, Linda Bernetich, Lynne Agoston, and Jon Benjamin, for their administrative, technical editing, and publishing work.

Line Break Charts

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Abstract

It is said that time-independent chart categories provide clear signals and objective setups. Their simple formation is beneficial, and visual analysis makes them look truly promising.

The question is whether such manual observations have proved effective in the past—whether the simplicity and objectivity that these charts offer can be tested on different environments.

This paper presents the research on line break charts. Three line break charts are widely known as one of the time-independent charting system. Signals and systems based on these charts are objective in nature, but it remains to be seen whether testing results are in accordance with subjective analysis.

Methodology

This paper conducts tests on various patterns of line break charts on data of 10 years, starting from 1 January 2005 to 31 December 2014 of two global indices: CNX Nifty and Nasdaq-100. One is a developed economy and another is emerging. The method of back-testing is preferred for arriving at certain decisions about subsequent tests. Testing the manual observation can be a start, and further tests will be conducted based on what we learn. More tables need to be presented than charts because of the testing methodology.

These 10 years of sample size include various phases of markets. Backtesting results are evaluated based on total return, average return and expectancy. Below is the formula to calculate expectancy:

Expectancy = (Probability of win x Average win) - (Probability of loss x Average loss) or (Risk reward ratio x Success ratio) - Failure ratio. The idea is to test whether the setup occurrences have produced positive expectancy. All backtesting results are gross figures. Learning will be discussed during the testing as well, and overall results will eventually be discussed.

Introduction

Three line break charts originated in Japan during the 19th century, and it was first brought to the Western world by Steven Nison when he published the book *Beyond Candlesticks*.(1) Three line break charts ignore time and volume, which is similar to one aspect of point and figure, Kagi and Renko charts. These time-independent charts plot only price and only when it moves as per certain criteria. Their method of plotting eliminates noise to a larger extent and produces easily readable patterns.

Unlike other time-independent charts, line break charts need only one variable to construct the chart known as reversal value. It is popular as the three line break charting method because of reversal value parameter typically used.

Three Line Break Chart

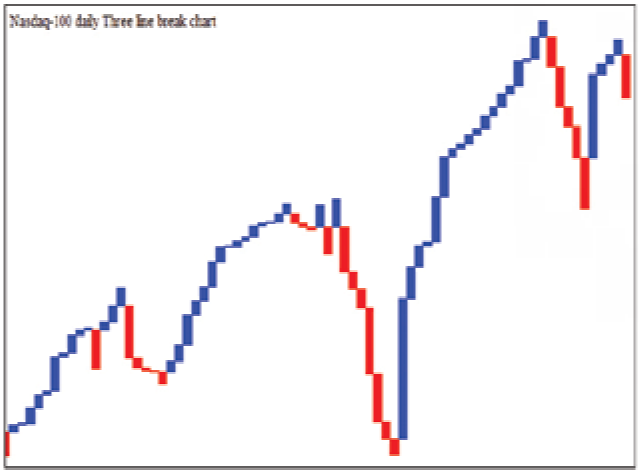
Construction

Line break charts display a series of vertical boxes (lines) that are based on changes in price. Normally, closing prices are used for plotting these charts. Rules for plotting three line break charts are as follows:

- If three consecutive bullish lines are formed, then a new bearish line is drawn only if the price falls below the lowest point of the last three bullish lines.
- If three consecutive bearish lines are formed, then a new bullish line is drawn only if the price rises above the highest point of the last three bearish lines.

The line break chart moves only when price trends or reverses by a certain criteria. It condenses the price action of price-time charts and displays only trending moves. Below (Figure 1) is an example of a three line break chart. Blue-coloured lines are bullish lines and red lines are bearish lines.

Figure 1. Nasdaq-100 Three line break chart of daily closing prices



These charts are visually very appealing and show the clear formations when trend is in place. By constructing a price chart in this manner, one can easily divide the price between bullish and bearish lines. It seems that bullish lines should occur more when there is uptrend and bearish lines when there is downtrend. There needs to be a test as to whether it has relevance or not with the state of the trend. Table 1 shows the yearly proportion of bullish and bearish line appearance in a daily three line break chart of CNX Nifty and Nasdaq-100 during the period from 1 January 2005 to 31 December 2014.

Table 1: Year wise appearance of bullish & bearish lines on daily Three line break chart

	CNX NIFTY			NASDAQ-100		
Year	Bullish lines	Bearish lines	YoY Return	Bullish lines	Bearish lines	YoY Return
2005	69.83%	30.17%	36.34%	52.48%	47.52%	1.49%
2006	78.81%	21.19%	39.83%	52.73%	47.27%	6.79%
2007	70.30%	29.70%	54.77%	71.72%	28.28%	18.67%
2008	33.33%	66.67%	-51.79%	41.24%	58.76%	-41.89%
2009	67.47%	32.53%	75.76%	67.24%	32.76%	53.54%
2010	67.50%	32.50%	17.95%	69.53%	30.47%	19.22%
2011	37.76%	62.24%	-24.62%	56.84%	43.16%	2.70%
2012	63.25%	36.75%	27.70%	65.42%	34.58%	16.82%
2013	50.43%	49.57%	6.76%	68.52%	31.48%	34.99%
2014	72.48%	27.52%	31.39%	66.67%	33.33%	17.94%

It is seen that the occurrence of bullish and bearish lines are in line with the market tone during the year. Bullish lines dominate in bullish scenarios, and bearish lines occur more in a down trending environment. They are close to equilibrium in consolidating phases.

Testing

Change of line is a simple and basic formation of line break charts. Three line break charts change the trend when an extreme price of the last three line is breached. A bearish line turning to bullish is 'Bullish change of line' & bullish line turning to bearish is 'Bearish change of line' formation. These formations can be backtested to observe whether trading their occurrences would yield anything.

Table 2 shows the backtested numbers of change of line formation. Bullish setup is entry on occurrence of bullish line and exit upon formation of bearish line. Bearish setup is entry on bearish line and exit upon occurrence of bullish line.

Table 2. Backtesting results of change of line formation on daily Three line break chart

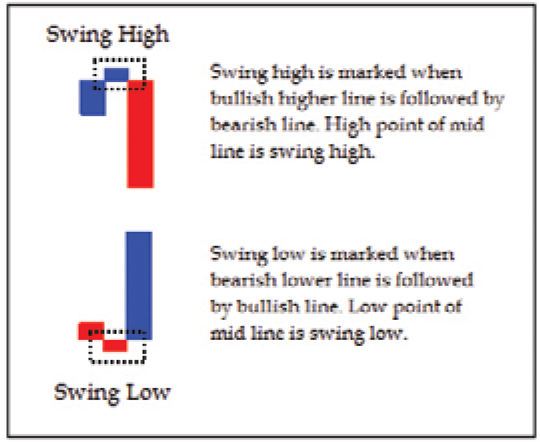
Instrument	Setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of Trades
CNX NIFTY	Bullish	150.59%	1.71%	52.27%	0.77	88
CNX NIFTY	Bearish	-21.59%	-0.25%	28.41%	-0.47	88
NASDAQ-100	Bullish	73.86%	0.72%	52.43%	0.36	103
NASDAQ-100	Bearish	-43.91%	-0.43%	28.43%	-0.51	102

*Bullish setup: Entry on Bullish change of line & Exit upon Bearish change of line
*Bearish setup: Entry on Bearish change of line & Exit upon Bullish change of line

Though occurrences of lines looked interesting, backtested results of change of line formations did not produce anything significant from a trading perspective. It can be beneficial for a particular period when an asset is trending, but the overall outcome is not encouraging. But the advantage is that charts are plotted with closing prices, and setups are more objective in nature; hence, things are close to the practical aspects of trading. If outcome from these charts proves to be positive, then it could be an interesting finding.

Line break charts are basically swing charts, and they easily display swing points. Swing high or swing low can be defined as shown in Figure 2.

Figure 2. Swing high and swing low patterns



Breakouts from swing points is a sensible setup that can be the greatest benefit of these charts. Breakout from the last swing high qualifies for the bullish swing high breakout, and breaching the previous swing low qualifies for the bearish swing low breakout. This gives clear entry and exit points that should prove beneficial in trending markets. Table 3 shows backtesting numbers when SAR (Stop and Reverse) strategy is applied using this strategy.

Table 3. Backtesting results of swing breakout strategy on daily three line break chart

Instrument	Setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of Trades
Nifty	Bullish Swing Setup	87.81%	3.51%	60.00%	1.19	25
Nifty	Bearish Swing setup	-64.80%	-2.59%	32.00%	-0.57	25
S&P500	Bullish Swing Setup	41.47%	1.22%	41.18%	0.07	34
S&P500	Bearish Swing setup	-76.74%	-2.19%	11.43%	-0.70	35

*Bullish swing setup: Entry on swing high breakout & Exit on swing low breakout
*Bearish swing setup: Entry on swing low breakout & Exit on swing high breakout

Setup is logical, but results of testing are not showing success if this strategy is adopted. Three line break charts reverse the downtrend when the price goes above the highest price of previous three lines. Similarly, uptrend is reversed when the lowest price of the previous three lines is breached. Hence, the number of prices required before reversal is four, and every reversal formation consists of four lines. But, not every reversal line occurs after a smooth trend of three consistent lines prior to the reversal. The combination of lines before reversal line talks about the price structure.

Patterns

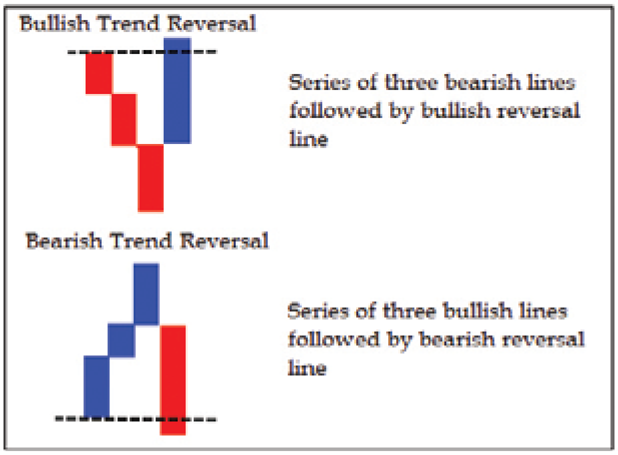
All possible reversal formations are defined and bifurcated in four-line reversal formations. Names of patterns are borrowed from traditional theories of technical analysis to make it simple to remember and understand.

Four-Line Reversal Patterns

Pattern 1: Bullish and Bearish Trend Reversal

As shown in Figure 3A, bullish trend reversal is a pattern when a series of bearish lines is followed by a bullish line. And bearish trend reversal is a pattern where a series of bullish line turns to a bearish line.

Figure 3A. Four line trend reversal patterns

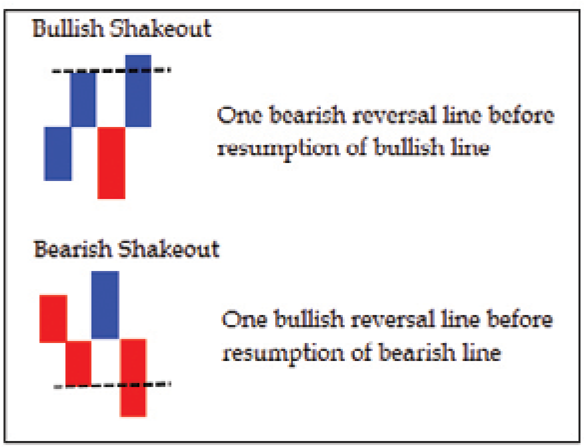


It is a typical three line break reversal pattern and is named a trend reversal because, unlike other patterns, the previous three lines in this case are in the same direction, so there was a trend before reversal. It can be understood now that all trend reversal patterns are change of line formations as well, but not all change of line formations are trend reversal patterns. Any pattern where the previous three lines before reversal are not in the same direction is not a trend reversal pattern.

Pattern 2: Shakeouts

Trends are not linear, and they keep shaking out the weak traders, even when the overall trend is strong. Figure 3B shows the shakeout pattern defined as four-line reversal pattern.

Figure 3B. Four line reversal shakeout reversal patterns

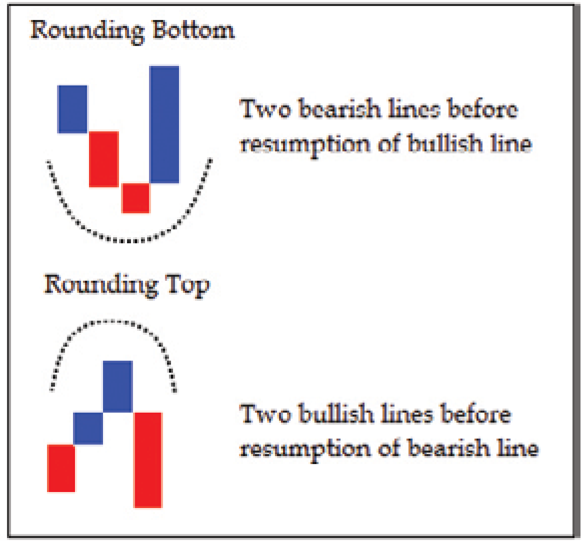


It is basically a formation of a single line against the trend, and then resumption of the previous trend. It shakes out the weak traders, hence the name. The pattern is complete only when the trend is resumed; hence, a bullish shakeout is confirmed only when a bullish line is formed, and a bearish shakeout is confirmed only when a bearish line is formed.

Pattern 3: Rounding Patterns

Price correction in an established trend is an opportunity for traders when identified. As shown in Figure 3C, two bearish lines between two bullish lines forms a rounding bottom pattern, the same way two bullish lines between two bearish lines form a rounding top.

Figure 3C. Four line rounding reversal patterns



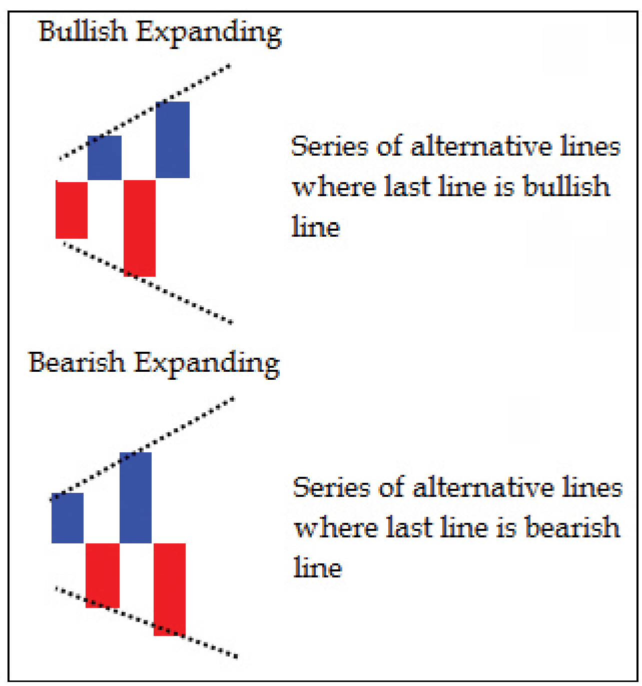
It is an extension to trap formation that suggests that some more "price" is spent in the correction. The name "Rounding" is given because pattern structure looks like the traditional rounding formation which has witnessed breakout.

Broadly, two types of price corrections are observed. One is where consolidating bars will occur, and time is spent without significant price correction before the resumption of a trend. A second is where price corrects with or without time correction before resumption of a trend. Three line break charts will not move and maintain the "status quo" in the former case. The latter case will result in "Shakeout" or "Rounding formation".

Pattern 4: Expanding Formation

This is rather a more interesting product of the line break charts. Three line break expanding pattern is a complex series of four lines, as shown in Figure 3D.

Figure 3D. Four line expanding reversal patterns

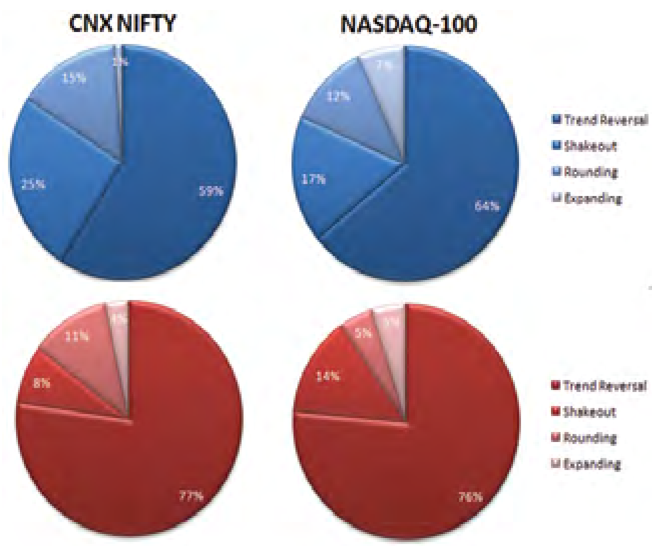


Whipsaws are not avoidable when such patterns are formed, but we come to know about expanding patterns when a series of alternative lines takes place. These are not very common patterns in terms of occurrences and suggests indecision among participants is resulting in a price noise. Name is expanding because subsequent lines make new highs and lows, so patterns look like traditional expanding formation. Expanding is a difficult phase for trend-following methods.

All three line break reversal formations will fall in one of the above mentioned four line reversal formations. The clear definition will allow us to bifurcate price data among them and test the occurrences. One major advantage is objectivity, which is helpful in many ways when it comes to visual or subjective analysis.

Figure 4 shows the percentage of occurrence of all four line formations during 10 years of our testing period.

Figure 4. Pie chart showing occurrences of four line reversal patterns during the testing period



It is seen that trend reversal has maximum occurrence. It needs to be tested whether such segregation reveals patterns of significance. Testing is effective if done from a trading perspective. Considering the above setups as entry point, it is required to define exit points. Following are two exit setups that can be of help.

1. Change of line: Exit when line changes after entry. This is a simple formation and important trait of line break charts.
2. Three consecutive lines against the trade: Three bearish lines in a row after a bullish trade, or three consecutive bullish lines after a bearish trade is a point to exit. This is considered because Shakeout and Rounding patterns require up to two lines against the trend, so their occurrence will be digested by considering this rule as an exit setup.

Table 4 shows the backtested numbers of all four line patterns with two exit setups defined above.

Table 4. Backtested numbers of all four line reversal formations

Setups		CNX NIFTY					NASDAQ-100				
Entry Setup	Exit setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of Trades	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of Trades
Bullish Trend Reversal	Exit 1	133.60%	2.57%	53.85%	1.09	52	70.29%	1.07%	56.06%	0.60	66
	Exit 2	187.07%	3.60%	59.62%	1.40	52	64.62%	0.99%	49.23%	0.23	65
Bullish Shakeout	Exit 1	5.59%	0.25%	45.45%	-0.01	22	11.22%	0.62%	50.00%	0.31	18
	Exit 2	20.10%	1.67%	41.67%	0.30	12	10.50%	0.75%	64.29%	0.24	14
Rounding Bottom	Exit 1	7.09%	0.55%	53.85%	0.57	13	-1.00%	-0.08%	58.33%	0.12	12
	Exit 2	-2.74%	-0.25%	36.36%	-0.35	11	-1.19%	-0.11%	45.45%	-0.12	11
Bullish Expanding	Exit 1	4.31%	4.31%	100.00%	0.00	1	-6.64%	-0.95%	14.29%	-0.80	7
	Exit 2	2.85%	2.85%	100.00%	0.00	1	-8.50%	-1.42%	33.33%	-0.54	6
Bearish Trend Reversal	Exit 1	-27.44%	-0.40%	26.47%	-0.53	68	-45.42%	-0.58%	23.64%	-0.59	78
	Exit 2	-45.72%	-0.68%	28.36%	-0.51	67	-66.35%	-0.85%	26.92%	-0.57	78
Bearish Shakeout	Exit 1	11.38%	1.63%	28.57%	-0.18	7	11.39%	0.81%	42.86%	0.08	14
	Exit 2	1.07%	0.15%	14.29%	-0.71	7	7.93%	0.61%	30.77%	-0.29	13
Rounding Top	Exit 1	-12.63%	-1.26%	30.00%	-0.65	10	-3.28%	-0.66%	20.00%	-0.70	5
	Exit 2	-20.43%	-2.92%	14.29%	-0.84	7	-4.23%	-0.85%	40.00%	-0.38	5
Bearish Expanding	Exit 1	7.09%	2.36%	66.67%	16.61	3	-6.60%	-1.32%	40.00%	-0.46	5
	Exit 2	-1.06%	-0.35%	33.33%	-0.44	3	-3.89%	-1.30%	33.33%	-0.55	3

* Exit 1: Change of line
* Exit 2: Three consecutive line against the trend

It is observed that exiting on three bearish lines proved better than exiting a setup on just one change of line for longs. Short setups are not seen generating positive outcomes. It seems that the exact opposite of long setup doesn't work for short trades, probably because the inherent nature of the market is bullish, and the downside is limited but the upside is infinite. Bullish trend reversal demonstrates an edge over other setups and change of line. The exit criteria of three reversal lines digests Shakeouts, Rounding and Expanding patterns after entry.

Swing breakout points are logical setups with a line break chart. Table 5 explores the idea of a combination of four line patterns along with a swing breakout strategy to check if anything in combination has got better say.

Table 5. Backtested numbers of swing breakout strategy with exit based on line break setups

Instrument	Setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of trades
CNX NIFTY	Exit 1	54.28%	0.89%	54.10%	0.53	61
CNX NIFTY	Exit 2	93.48%	2.75%	47.06%	0.77	34
NASDAQ-100	Exit 1	30.49%	0.43%	52.11%	0.26	71
NASDAQ-100	Exit 2	38.43%	0.91%	54.74%	0.44	42

*Exit 1: Bearish change of line
*Exit 2: Three consecutive bearish lines

Table 6. Backtested numbers of four line patterns with swing breakout as exit setup

Instrument	Entry Setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of trades
CNX NIFTY	Bullish Trend Reversal	179.44%	5.13%	51.43%	1.24	35
	Bullish Shakeout	30.25%	2.16%	42.86%	0.66	14
	Rounding Bottom	-11.28%	-1.13%	50.00%	-0.18	10
	Bullish Expanding	0.00%	0.00%	0.00%	0.00	0
NASDAQ-100	Bullish Trend Reversal	107.81%	3.08%	48.57%	0.73	35
	Bullish Shakeout	-2.38%	-0.15%	43.75%	-0.17	16
	Rounding Bottom	11.94%	1.19%	40.00%	0.15	10
	Bullish Expanding	3.63%	0.52%	28.57%	-0.33	7

It can be otherwise as well. Table 6 shows entry with four line patterns with swing breakout as an exit strategy.

Swing exit improve the numbers. Table 7 shows numbers when a swing breakout exit strategy is combined with three lines against the trade, that means, either of them will suffice the exit criteria.

Table 7. Backtested numbers of four line patterns with exit as swing breakout or 3 consecutive lines against trend

Instrument	Entry Setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of trades
CNX NIFTY	Bullish Trend Reversal	188.29%	3.62%	55.77%	1.38	52
	Bullish Shakeout	28.06%	2.00%	35.71%	0.08	14
	Rounding Bottom	0.87%	0.08%	45.45%	-0.06	11
	Bullish Expanding	2.85%	2.85%	100.00%	0.00	1
NASDAQ-100	Bullish Trend Reversal	77.57%	1.19%	46.15%	0.24	65
	Bullish Shakeout	5.90%	0.37%	56.25%	0.30	16
	Rounding Bottom	6.60%	0.60%	54.55%	0.42	11
	Bullish Expanding	-11.07%	-1.58%	14.29%	-0.83	7

This exit condition shows more positive numbers. The setup becomes logical because having bearish swing point breakout as one of the exit conditions will ensure exit upon any bearish four line reversal pattern, if it is occurred before three consecutive bearish lines. Let us call it '3LB long exit' for further reference in this paper.

It is logical to trade setups when risk is defined and affordable. The percentage of risk is not known when entry setup is triggered in these charts. The magnitude or size of the line can also play a role in deciding to enter or exit. The occurrences can be tested further to consider undertaking trades below certain reversal percentage only.

Performance is improved when more risk is accepted. Numbers prove the idea that more risk is more rewarding, and return per trade gets improved. Various reversal percentage criteria can be applied to take these tests further. Positive expectancy for long setups is seen, but it is not reached for short trades over a period. The length of the line is an important point in line break charts.

Length of Lines

Other time-independent charting techniques like point and figure and Renko construct the charts using fixed values known as Box value and Brick value, respectively, along with reversal values. Line break charts plot actual prices instead of using the fixed values for plotting. This is the significant feature of line break charts and enable them to produce line of varying lengths that becomes very important tool for the price structure. But this also comes with an issue. The major problem with line break charts from trading perspective is the length of lines. They are like chart stoppers. At times, a huge line would appear that just stops the chart from moving forward, mainly because price is correcting but not up to the length of last three lines to produce another line. We call these charts as noise free but very large line that doesn't allow reversal to happen also filters out many significant price actions.

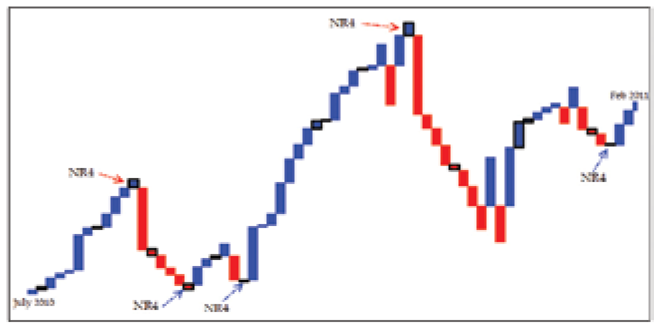
These lines can broadly be classified as Narrow lines and Wide lines. As the name suggests, narrow lines are basically the lines with relatively narrow size. An instrument that is going up and forming new higher prices will keep producing continuation lines. A marginal higher price will produce the narrow line. The formation of narrow line brings reversal level closer. Reversal narrow lines are not very common and indicate serious price consolidation or lack of interest among participants for the instrument.

Continuation wide lines indicate strong trends. Reversal wide lines are usual because price is required to breach extreme levels of previous three lines to mark reversal. Stops after such lines become wider compared to other lines. Basically a line in Line break chart is a difference between two closing prices, hence large length of line also indicate strength in the trend.

Objective definition of wide and narrow setup is difficult. The concept is basically relative and subjective in nature. Traditional concepts of NR4 and W4 can be of help here. NR4 is a usual price-time chart setup where current range (difference between high and low price) of price is narrowest among last four ranges. W4 price also indicates widest range of price among last four. NR4 in line break charts is narrowest line among last four lines and W4 is widest line among last four. This can make us define the length of lines and enable us to back test them.

It is observed on the chart that occurrence of narrow line before reversal make it significant. Setup is shown in Figure 5 of EURUSD Three line break chart.

Figure 5. EURUSD daily Three line break chart showing NR4 pattern before reversal line



The idea can be tested now with the help of NR4 setup. Table 8 below shows the result of long setups where NR4 line is formed before Bullish change of line.

Table 8. Backtested results of NR4 followed by bullish change of line

Instrument	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of trades
CNX NIFTY	53.59%	3.15%	64.71%	1.80	17
NASDAQ-100	42.95%	1.53%	53.57%	0.56	28

* Exit setup: 3LB long exit

Numbers look interesting and outperform the usual reversal hence there is something to pay attention when reversal occurs after NR4 line. Various other occurrences can be tested using this. Understand that not all reversal patterns are also W4, and they can be tested separately. Of course, infinite are the ideas. Clear definitions allow us to test our imaginations and observations. Short setups need more digging. This leads to the idea of different exit setups or profit exits. Various profit exit methods such as one–three lines coming in favour were tested, which proved effective. It is learned that short setups need aggressive exit methods. Profit booking method in long setups results in significant drop in yield per trade hence should be avoided. They are better ridden with trailed exits. Other Four line patterns like Rounding, Shakeout and Expanding formations can be tested as separate entry setups. Table 9 below shows the backtested numbers of testing their occurrence separately with exit as change of line formations or when three lines come in favour as a profit exit.

Table 9. Other four lines patterns tested with exit as change of line or 3 lines in favor on three line break chart

Instrument	Entry setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No. of trades
CNX NIFTY	Rounding Bottom	27.27%	2.10%	100.00%	1.00	13
	Bullish Shakeout	-2.86%	-0.13%	54.55%	0.04	22
	Bullish Expanding	1.18%	1.18%	100.00%	0.00	1
	Rounding Top	2.01%	0.20%	70.00%	0.05	10
	Bearish Shakeout	2.50%	0.36%	42.86%	-0.06	7
	Bearish Expanding	8.53%	2.84%	100.00%	0.00	3
NASDAQ-100	Rounding Bottom	2.60%	0.22%	75.00%	0.05	12
	Bullish Shakeout	1.33%	0.07%	55.56%	0.15	18
	Bullish Expanding	-4.17%	-0.60%	57.14%	-0.14	7
	Rounding Top	0.03%	0.01%	60.00%	0.20	5
	Bearish Shakeout	18.92%	1.35%	57.14%	0.83	14
	Bearish Expanding	-0.79%	-0.16%	40.00%	-0.23	5

High-Low Charts

We only considered closing prices while constructing Line break chart which is the traditional way of doing it. Point & Figure is another method of plotting noiseless charts. A.W.Cohen (2) introduced High-Low P&F chart in his brilliant work. Same construction logic can also be used in Line break charts. Three line break High-Low charts ignore closing price and plot charts only using high and low prices. Only high price is considered for plotting if last line is bullish and only low price is considered if last line is bearish.

It is natural that chart constructed with High-low price are wider than chart plotted with closing prices. All above mentioned setups are valid on these charts as well which can be back tested. The length of line issue is minimised but there is another issue. These charts are plotted using high & low prices and we don't know whether high has occurred first or low while plotting them. Reversal line is not plotted when both meet requirement on a particular day. For this reason it is better that only chart plotted with closing prices are focused upon for back testing.

Charles Dow considered the daily close as the most significant price and relied exclusively on them. The usual line chart that plots only closing prices is one of the oldest and most important method of plotting prices. Also, as Murphy argues, "Many chartists believe that because the closing price is the most critical price of the trading day, a line (or close only) chart is more valid measure of price activity." (3) Line break charts filters noise from usual line charts and allow us to define setups using combination of closing prices.

Timeframe

We considered daily closing prices for plotting. However, it can also be plotted for intraday timeframes of any length. The same way it is also possible to plot it using monthly, weekly and yearly prices.

Other Reversal Values

Five, Four and Two Line Reversals

Charts can be plotted using other reversal values also instead of usual three lines as a reversal. Four and Five line reversal charts can be plotted and tested. Noise will be filtered further in these charts and change of line formations becomes interesting. But length of line issue will be magnified that limits their practical utilisation, though some backtesting numbers are encouraging.

Two line break charts are quite interesting and patterns we discussed above are applicable to them also with few variations. It has more to do with length of second line in a four line structure. All these charts can be back tested in the same manner.

One Line Reversal Charts

One line break charts are of separate importance and different from other reversal values in nature. To an extent they deals with length of line issue in a better manner. Reversal criteria of 3 is made that of 1 while plotting One line break charts.

The general rules for plotting a one line break chart are as follows:

- If the price exceeds the previous line's high price, a new bullish line is drawn.
- If the price falls below the previous line's low price, a new bearish line is drawn.
- If the price does not rise above nor fall below the previous line, nothing is drawn.

A One line break chart will produce more lines compared to a Three line break chart. So there is more noise but then, more information as well. Objectivity and possible combination of lines remain advantageous and allow us to test various occurrences and develop our understanding of market behaviour.

One line break charts are more useful compared to Three line break charts when very a wide line is produced in latter charts or when the trend is horizontal in nature and one wants to analyse the structure. Four line patterns logic doesn't apply to One line break charts. Change of line is more of noise in these charts, but it remains to be seen whether the formation can prove useful from a trading perspective. Table 10 shows the back tested numbers of change of line formations on one line break chart.

Table 10. Backtested numbers of change of line formation on daily One line break chart

Instrument	Setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	Bullish	150.02%	0.47%	44.30%	0.14	316
CNX NIFTY	Bearish	-24.85%	-0.08%	27.22%	-0.48	316
NASDAQ-100	Bullish	-16.37%	-0.05%	34.99%	-0.32	343
NASDAQ-100	Bearish	-134.31%	-0.39%	22.22%	-0.65	342

*Bullish setup: Entry on Bullish change of line & Exit upon Bearish change of line
*Bearish setup: Entry on Bearish change of line & Exit upon Bullish change of line

As expected, it is of little importance on these charts as well. But swing breakouts seem more relevant being the most logical formation on these charts. Breakouts will be little early and there will be more occurrence comparatively. Table 11 shows the backtested numbers of Swing breakout points using SAR method.

Table 11. Backtested numbers of swing breakout strategy on daily One line break chart [1]

Instrument	Setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	Bullish	132.88%	1.51%	47.73%	0.46	88
CNX NIFTY	Bearish	-50.12%	-0.57%	27.27%	-0.53	88
NASDAQ-100	Bullish	46.83%	0.51%	38.46%	-0.10	91
NASDAQ-100	Bearish	-74.79%	-0.82%	23.08%	-0.65	91

*Bullish swing setup: Entry on swing high breakout & Exit on swing low breakout
*Bearish swing setup: Entry on swing low breakout & Exit on swing high breakout

Long setups showing some positive outcome but short trades don't earn using this method as well. Four line bullish trend reversal formation can be defined in one line break charts when reversal line has breached the extreme price of previous three lines. It is stronger than usual change of line formation.

One line formations can help in analysing horizontal formations or price structure in consolidation mode. Breakout strategy from certain number of previous lines can be formed for these kinds of setups. Table 12 shows back tested numbers of 10, 20 and 50 lines bullish breakout. Reverse breakout is used as an exit point.

Table 12. Backtested numbers of Line breakout bullish setups on daily One line break chart

Instrument	Setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	10 lines setup	179.79%	3.27%	52.73%	1.48	55
	20 lines setup	124.02%	4.00%	58.06%	1.32	31
	50 lines setup	104.46%	11.61%	55.56%	2.18	9
NASDAQ-100	10 lines setup	55.24%	0.91%	47.54%	0.20	61
	20 lines setup	60.65%	1.96%	54.84%	0.58	31
	50 lines setup	75.85%	6.90%	63.64%	1.73	11

*10 lines setup: Entry on 10 lines bullish breakout & exit upon 10 lines bearish breakout
*20 lines setup: Entry on 20 lines bullish breakout & exit upon 20 lines bearish breakout
*50 lines setup: Entry on 50 lines bullish breakout & exit upon 50 lines bearish breakout

The concept is similar to various channel breakout methods and looks impressive. Lines in one line break charts will vary from usual closing prices due to noise filtration method. I have taken round numbers for testing this concept that are sufficient enough to give an idea. More such numbers based on various theories can be tested.

Alternate Lines

Four line expanding formation is not relevant on one line break charts. But the setup becomes that of alternate lines, which is a very important product of these charts. It displays price noise or indecision prevailing among market participants which shall eventually get a clear way. The area of alternate line formation is of importance from support and resistance perspective for subjective analysis.

Various alternate lines were backtested to check whether it can be traded upon occurrence. Bullish alternate line is formation where last line is bullish and bearish alternate line is where last line is bearish. There can be 4-6 alternate line formations in one line break chart as shown in table 13. It is very uncommon to find anything above that. Even these are rare occurrences but provide some informative setups when traced.

Table 13. Backtested numbers showing performance of various alternate lines setup with swing exit strategy on daily one line break chart

Instrument	Alternate lines setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	Bullish 4	102.34%	3.20%	43.75%	0.96	32
	Bullish 5	59.36%	4.57%	61.54%	8.87	13
	Bullish 6	10.13%	3.38%	66.67%	7.26	3
	Bearish 4	40.55%	1.19%	26.47%	-0.15	34
	Bearish 5	24.46%	2.72%	44.44%	1.80	9
	Bearish 6	16.41%	5.47%	66.67%	20.09	3
NASDAQ-100	Bullish 4	4.95%	0.12%	25.58%	-0.47	43
	Bullish 5	9.80%	0.52%	36.84%	-0.03	19
	Bullish 6	4.23%	0.85%	60.00%	1.00	5
	Bearish 4	13.01%	0.34%	31.58%	-0.21	38
	Bearish 5	0.75%	0.07%	36.36%	-0.25	11
	Bearish 6	-0.46%	-0.12%	25.00%	-0.52	4

Bullish 4 in Table 13 is 4 line bullish alternate pattern & bearish 4 is 4 line bearish alternate pattern. Same way 5 and 6 line alternate patterns are also tested. Even bearish setups are tested for longs because it is observed that short trades don't produce positive numbers for entry upon such occurrences. It seems from results that alternate lines on one line break chart is an interesting setup for bulls to scan.

Indicators

A line of line break charts can easily be called as candle due to its look and such a widespread or usefulness of candlestick charts. A line in Line break chart is basically a length between two closing prices. All indicators that are drawn on price-time charts can also be drawn on Line break charts. Formula remain same with most of the indicators but logic of construction and few settings can vary. Table 1 with percentage of line occurrence suggested that bearish lines dominate in down trending markets. Idea lead to trend identification tool to filter patterns. Indicators help us in identifying the trends. And objective setups using combination of lines can complement them. Their application is tested with 3LB long exit strategy for bullish setups and change of line or two lines in favour for bearish setups.

Moving Averages

Moving averages can be drawn on Line break charts using number of lines instead of bars or candles. The moving average is the most simple and basic tool to identify trend. Lines above the moving average can be treated as uptrend and vice versa. Bullish change of line above simple moving average is a setup consisting a bullish pattern in an uptrend. Table 14 shows numbers of bullish change of line above 20 line simple moving average and bearish change of line below 20 line simple moving average.

Table 14. Backtested numbers of moving average setups on daily three line break chart

Instrument	Entry setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	Bullish Col change above 10 SMA	141.06%	3.92%	58.33%	2.06	36
	Bearish Col change below 10 SMA	-18.74%	-0.40%	68.09%	0.18	47
NASDAQ-100	Bullish Col change above 10 SMA	57.12%	1.08%	45.28%	0.26	53
	Bearish Col change below 10 SMA	8.46%	0.16%	66.67%	0.43	54

Pull back setups can also be defined using moving averages. Rejection of 10 line simple moving average on three line break charts is one such example.

RSI

RSI developed by J. Welles Wilder[4] is the most popular and widely used momentum indicator. Table 15 shows the back tested numbers when 14 line RSI crosses its mid-value 50 or falls below it on Three line break chart. 14 period is used because it is widely followed.

Table 15. Backtested numbers of 14 line RSI setup using 3LB long exit on daily three line break chart

Instrument	Entry setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	Crossover above 50	145.29%	3.83%	60.53%	1.67	38
	Crossover below 50	12.33%	0.32%	76.92%	0.83	39
NASDAQ-100	Crossover above 50	65.64%	1.56%	45.24%	0.36	42
	Crossover below 50	12.10%	0.26%	78.72%	0.83	47

ADX

Another indicator developed by J. Welles Wilder[5], ADX is widely used to gauge the strength of the trend. Traditional formula to plot ADX uses ATR (Average True Range), which is not applicable to Line break charts. Average range of line is used instead of ATR to plot ADX on Line break charts.

Table 16 shows performance of ADX positive and negative DMI crossovers on line break charts.

Table 16. Table 15: Backtested numbers of 14 line RSI setup using 3LB long exit on daily three line break chart

Table 16: Backtested numbers of 14 line ADX DMI setups using 3LB long exit on daily Three line break chart

Instrument	Entry setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	Positive Crossover	131.46%	3.76%	54.29%	1.38	35
	Negative Crossover	31.29%	0.85%	89.19%	0.51	37
NASDAQ-100	Positive Crossover	81.70%	1.90%	46.51%	0.65	43
	Negative Crossover	-24.87%	-0.51%	63.27%	-0.02	49

Bollinger Bands®

John Bollinger's[6] Bollinger Bands® are the most logical channel indicator for analysing price behaviour. Pull back setups can be defined using change of line formation from bands. Rejection of lower band by bullish change of line is a pullback setup.

Table 17 shows the numbers when price reversed from 20, 1.5 lower Bollinger band in three line break charts.

Table 17. Backtested numbers of 20 S, 1.5 SD Bollinger Bands® setup using 3LB long exit on daily Three line break chart

Instrument	Entry setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	Bullish change of line from lower Bollinger Band	178.67%	5.58%	65.63%	2.85	32
	Bearish change of line from upper Bollinger Band	-36.02%	-0.90%	52.50%	-0.20	40
NASDAQ-100	Bullish change of line from lower Bollinger Band	78.59%	2.91%	59.26%	1.22	27
	Bearish change of line from upper Bollinger Band	10.66%	0.22%	62.50%	0.40	48

Average Gain Loss Lines

If a number of bullish lines start dominating it gives an indication about the direction of breakout. Average gain loss line is an indicator that can help in analysing the state of the trend.

Average gain loss line will witness positive crossover when average gains from positive lines of a certain period will exceed losses. Table 18 shows the backtesting numbers of positive and negative crossovers of the indicator.

Table 18. Back-tested numbers of 10 period cve gain loss line using 3LB long exit on daily three line break chart

Instrument	Entry setup	Total Return	Ave return per trade	Success Ratio	Expectancy	No of Trades
CNX NIFTY	Positive Crossover	137.78%	3.20%	51.16%	1.20	43
	Negative Crossover	5.67%	0.11%	78.00%	0.04	50
NASDAQ-100	Positive Crossover	55.74%	1.91%	44.68%	0.25	47
	Negative Crossover	34.14%	0.61%	80.36%	0.29	56

Figure 6 shows average gain loss line indicator applied on dollar index.

Figure 6. Dollar Index daily Three line break chart along with 10 period Average Gain-loss line

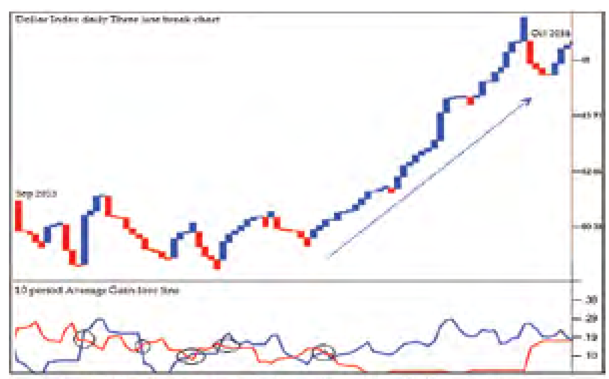
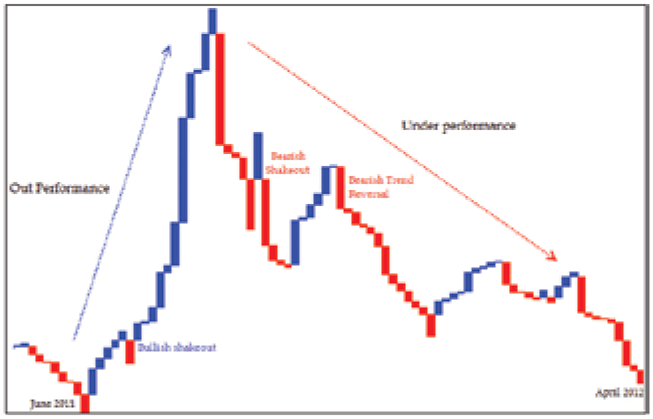


Figure 6: Dollar Index daily Three line break chart along with 10 period Average Gain-loss line

Relative Strength

It is a fascinating idea to buy strength and sell weakness. A lot is written on relative strength charts. Line break relative strength charts can be plotted using ratio of two instruments. Setups that we have discussed in the paper can be implemented and back tested on relative strength charts also. Combination of line break setups and even plotting of indicators can prove helpful in analysing relative strength charts further. Figure 7 is the Ratio line of Gold and S&P 500, which is plotted as Three line break chart.

Figure 7. Gold/ S&P 500 line break relative strength chart

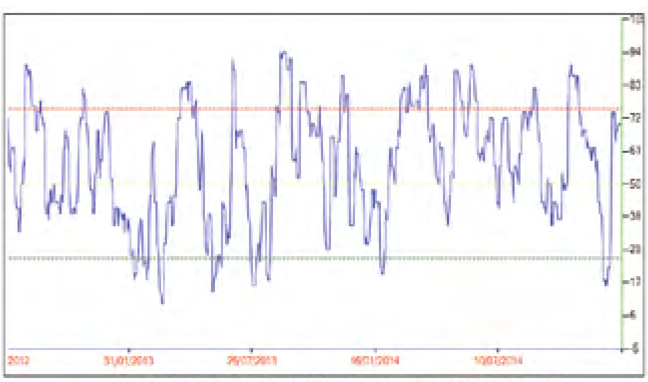


When the ratio line goes up, it indicates that the numerator is outperforming denominator and vice versa. It can also help in studying Inter market relationships and in analysing the relationship between various asset classes. The main advantage of Line break Relative strength charts is the clear objective setups that it provides that can also be back tested in a similar manner.

Breadth

Breadth indicators are the most important tool of any trading kit. It can give us the idea about state of the trend and sentiment extremes. Extreme positivity indicates over optimism and extreme negative suggests panics or high pessimism. There are many types of breadth indicators widely used to analyse these sentiment extremes. Line break charts can contribute here. Stocks with number of bullish lines on Line break charts in a group can be counted and plotted on a daily basis to create a breadth indicator. Figure 8 is a Three line break Breadth indicator applied to Indian stock market indices CNX Nifty.

Figure 8. Three line break chart breadth indicator showing percentage of bullish lines of CNX Nifty group stocks



Extreme positivity zone can be marked when the indicator is above 75, and overpessimism can be marked when it is below 25. These zones can be used for fine tuning exits and filtering entries. One line break breadth indicator can also be applied to analyse short-term sentiment phases.

Discussion

Various tests have been conducted throughout the paper. Simple change of line formation that was visually appealing was not effective on tests. Learning led to identification of Four line reversal patterns that differentiates various reversal formations. Names and concepts are borrowed from traditional theories and based on work done by great researchers.

Tests on various line combinations on Three line break charts resulted in logical setup for longs. But it is learned that short trades need different treatment and counter to what may work for longs doesn't equally work for shorts in these charts. Tests show that quick exit and profit booking can improve results of short trades on daily timeframe. Tests on setups restricted by a certain reversal percentage indicated that higher risk demonstrates a better reward compared to affordable setups with lower risk.

The traditional setups gave us the idea to define length of lines. Though Three line break is the most popular method, varying the reversal value produces different setups. One line break charts are useful with Line breakout trend-following systems. Alternate lines, NR4 setups and tests of Four line combinations suggested treatment to occasional setups. Results were improved when line combinations were tested using indicators on Line break charts possibilities of defining such setups is infinite and it suggests the wide scope for applying techniques on Line break charts. Long pull back setups were found effective when tested using indicators.

Simplicity of line break construction can help in defining setups of Relative strength charts. Breadth indicator is also possible to plot using Line break charts that can help in filtration of fresh entries. Backtesting certainly doesn't guarantee future and there are many methods of analysing them. Idea is to conduct test of occurrences and not just to rely on subjective analysis to define setups. Tests were conducted on rounded or widely followed parameters because idea is not to design a trading system but to talk about possibilities and scope of this charting technique.

Summary

Many of times things looks very appealing visually. Testing the observations is sometimes very complex or tedious. Simplicity of Line break charts made testing of various setups possible. Different tests that we have conducted in this paper will give an idea about what is most effective to consider while viewing or analysing Line break charts.

A major advantage of Line break construction is objectivity and the possibility of designing various setups using a combination of lines. Many combinations can be designed using the basic patterns that we have discussed. Classification of reversal formations can enrich the pattern library for this chart category.

All techniques are tools to develop our market understanding. Several discussions in the previous sections can help us know more about charts and market behaviour. Some tweaking of the rules may be required while applying it to different instruments. Line break charts can complement various kinds of methods, theories and also subjective analysis. Patterns are formed at closing prices that makes it simple to read, test, and implement.

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Software and Data

Charting software and chart courtesy of TradePoint and Definedge Solutions

Data courtesy of Bloomberg and Reuters

Entropy of Market Profile: A New Method of Determining Trend Days in Futures Markets

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Abstract

Steidlmayer, Dalton and other authors claim that the initial hour of a trading day—called the Initial Time Range, or IR—is sufficient to determine the probability that a trend will develop. In our experience, however, the conventional IR provides too little information and occurs too late in the trading day to make trades viable. This paper proposes a new method of determining Trend Days (hereafter called Entropy of Market Profile, or EMP) that builds on Steidlmayer's original discoveries by incorporating price action on prior days.

EMP is calculated by dividing the area of Market Profile (accumulated quantity of prints) by the height of the daily Market Profile. A Trend Day is considered to have occurred when the EMP value is low. So, in this thesis, a Trend Day usually occurs when EMP 2.0 is less than '-1σ' from the mean. Tests were conducted on four futures markets—Nikkei 225, 10-Year JGB, Gold and Crude Oil—to determine under what conditions EMP 2.0 occurred. Those tests confirmed a significant difference between the price fluctuations on the day of EMP 2.0 and those one to three days before. Tests were also conducted to determine under which trend phase EMP 2.0 was likely to occur on five-day moving averages.

These tests concluded that the new method improved on the conventional method in the Nikkei 225 and showed no significant difference in the other three markets.

Introduction

Purpose of present study

This study introduces a new method of determining the probability of a trend change based on the concept of Market Profile. We have named this new method "Entropy of Market Profile" (hereafter referred to as EMP) to draw an analogy with the concept of entropy in thermodynamics. In thermodynamics, entropy refers to the degree of disorder or randomness in a system. In technical analysis, entropy refers to the probability that a specific type of price behavior—such as a Market Profile Trend Day—may develop in a financial market or security.

The daily basis, CBOT method [4, 18] described by Steidlmayer [15] and Dalton[5], determines day-type figures for Mode, Value Area, Initial Time Range (IR) Movement, and blank range of a Market Profile.[8,11] Using Market Profile, it may be possible to predict a Trend Day by observing the movement of IR if a position is taken immediately after IR. But we cannot recommend this method because, in our experience, taking a position immediately after IR provides insufficient information and generates signals too late in the trading day to make trades viable. To correct this problem, we propose that price activity on prior days be used to determine a Trend Day.

Steidlmayer stated, "Market Profile tries to identify the underlying conditions of the current market's movement for continuation or change." [15] Dalton said, "There are two types of Trend Days: the standard Trend Day and the Double Distribution Trend Day. The most important feature of a standard Trend Day is the high level of directional confidence that is evident throughout the day."[5] Trend Day—which is defined as the day on which the price change is more than double its IR—is considered to be related to the start of a larger trend and therefore to increased profit potential. So this thesis focuses on analyzing the Trend Days of the Market Profile.

We agree that the four types of IR pattern can be used to determine the probability that a trend is developing, as Steidlmayer, Dalton, and the other authors claim. However, our long experience suggests that one hour of price activity is too little to generate a reliable forecast. So, in this thesis, we propose a new method of defining and quantifying Trend Days and Market Profile movements (the EMP method). We verify statistically the relationship between the price action prior to the occurrence of a Trend Day and EMP. This verification is significant because—to our knowledge—no CME literature (which has copyright of Market Profile) or LDB literature defines the conditions under which a Trend Day occurs.[19]

Background and definition of the problems

"Market Profile" is an intra-day charting technique developed by J. Peter Steidlmayer, a trader at Chicago Board of Trade in 1980. It incorporates histograms defined by price ranges.[14] Steidlmayer attempted to determine market value as it developed during a daily trading session. According to his definition, a bell-shaped distribution indicates a "Normal Day". Figure 1 shows the pattern of a typical daily figure for Market Profile.[4] Predicting a Trend Day in "Initial Time Range", during the first hour of the trading day, allows one to realize a trading opportunity. According to Steidlmayer, "Traditional technical analysis tries to predict the future based on the past trend. Market Profile tries to identify the underlying conditions of current market movements likely to precede continuation or change." [15]

There are several kinds of Entropy: thermodynamic entropy, the entropy of classical and quantized statistical systems, and the entropy of information. This thesis was investigated by applying the second law of thermodynamics by Clausuisu's investigation that "Change in Entropy=Heat supplied/ Temperature."[1,16] Generally, candlestick charts and oscillators are utilized to analyze the market; however, there is no oscillator that works with EMP so far. We would like to research possible oscillators in the future. Market Profile is a suitable analytical method to express EMP because all market energy movement is condensed in 30-minute prints.

Figure 1. Day types figure example

Normal Day Type			Trend Day Type	
Typical Normal (A Balanced Situation)	Normal Variation (Combination of Balance and Imbalance)	Neutal (A Balanced Situation)	Double Distribution Day	An Imbalaced Situation
A	A	G	A	A
A	AL	AG	A	aDe
A	ADL	AG	A	ADCDE
ADJL	ABKL	aBEG	A	AbcdE
ABDIJKL	ABDKL	ABEG	AC	ABCE
ABCDeFGHIJKL	abcDKl	ABEFgL	aBc	ABE
aBCdEFghIJKL	ABCdKL	ABCDFIGL	ABCDF	FH
AbcEfGHIJKL	ACDEKL	ABcDeFGhL	AbCDe	EFH
ABCEFGHL	ACDeFIK	AbCDEFGHIL	ABCDE	EfGH
ABEL	ACDEfIK	ABCDFGHIJKI	ABCDE	FGh
A	AEFIJK	BCDFGHIjKL	BCdE	FGH
A	EFIJ	CdFGHIJKL	BCE	FGH
A	Egij	CDFGHIJKL	BCEf	FgH
A	GhI	CGHIJKL	BF	FGH
	GHI	HK	F	FGHL
	GHI	H	FHL	FHL
	G		FGhL	FHIL
	H		FGHIL	HIL
	H		FGHIL	HIKL
	H		FGHIL	HIKI
			FgHIL	HIKL
			FGHIL	IKL
			FHIJL	IKL
			HIJL	IKL
			HIJL	IJK
			IJL	IJK
			IJL	IJK
			IJKL	IJK
			IJKL	IJK
			JKI	IJK
			JKL	IJK
			JK	IJ
			JK	I
			JK	I
			J	I
			F	I
			F	I
			F	I
				I
				I

*Light grey area shows Initial time Range.
*Red range shows Value Area, 70% movement price.
*Bold-faced letters show Mode that is biggest volume price.
*In this thesis, Double Distribution Day was included in Trend day.

Materials and Methods

Markets applied in this analysis

Nikkei 225 futures, JGB futures, Gold futures and Crude Oil futures were used in this analysis because those markets are highly liquid and their intraday price movement is especially focused. The intraday price of each market was gathered as shown below. Tick data is more accurate to utilize, but 1-minute data was utilized as well. 30-minute data was used instead of 1-minute data if the 1-minute or tick data was not available. The currency market was avoided due to lack of volume data and no fixed timeframe. 30-minute data was utilized when 1-minute data was not available.

- Nikkei 225 futures (active month): 341 days data from 13-May-2014, 1-minute data, 9:00-15:15, unit is 10 yen, from QUICK
- JGB futures (active month): 163 days data from 1-Feb-2015, 1-minute data, 8:45-15:02, unit is 0.01 yen, from QUICK
- COMEX Gold futures (active month): 324 days data from 1-Jul-2014, 30-minute data, 8:00-13:00, unit is 0.5 dollar, from Bloomberg
- NYMEX Crude Oil futures (active month): 322 days data from 1-Jul-2014, 30-minute data, 9:00-14:30, unit is 0.05 dollar, from Bloomberg

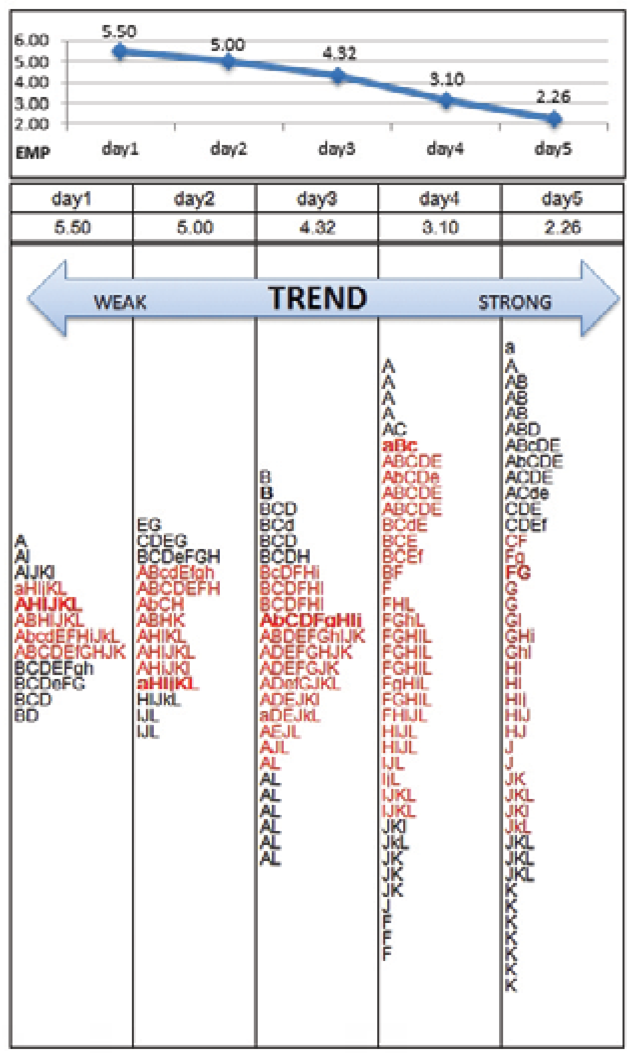
Formula of EMP

$\lceil dS=dQ/T \rfloor \rightarrow EMP=A/R$[12]

- dS =EMP, for accumulation of energy.
- dQ=A, for gross area of Market Profile on intraday (1 single print was counted as 1 unit.)
- T=R, for range of intraday. (1 unit was compensated to "High–Low" to apply accurate range for calculation.)

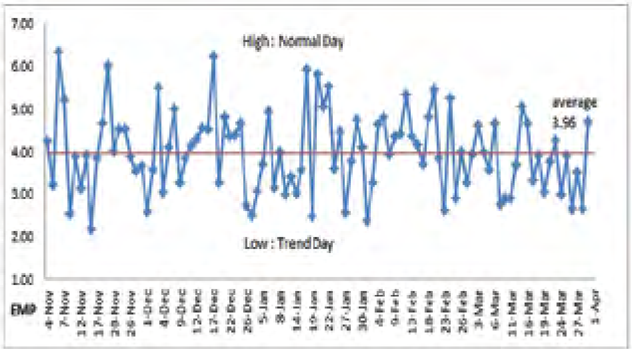
Figure 2 shows a strong relationship between EMP and day type figures in Nikkei 225 futures. An indication is that Trend Day figure occurs in low EMP day and that typical type Normal Day occurs in high EMP day. Figure 3 shows the daily transition of EMP for Nikkei 225 futures. The shape is like a zigzag pattern. The shape of EMP for other markets such as JGB, Gold, and Crude is also similar to the Nikkei 225's like this. According to Figure 3, there is certain high limitation of EMP. So EMP starts to decrease when approaching the limitation. EMP does not stay in High/Low value for a long time.

Figure 2. EMP and day type figure example



*Red range shows Value Area, 70% movement price.
*Bold-faced letters show Mode that is biggest volume price.

Figure 3. Transition of EMP



*Nikkei 225 futures, 04/11/14-01/04/15 (100 days): data from QUICK

Definition of EMP 2.0

As shown in Figure 4, EMP of four markets shows normal distribution. Then it was found that Trend day occurred if EMP was less than 3 (=2.XX...=herein after mentioned as EMP 2.0). When the standard deviation was in the range of -1σ in each market, it was determined that EMP was in the range of about less than 3. So in this thesis, EMP 2.0 is considered as condition of Trend Day occurrence.

Method of statistical test

Test of null hypothesis

According to the above, data were analyzed by using common statistical procedures "R-language (ver.3.2.2 Windows 64-bit)" to verify the null hypothesis test about EMP 2.0 and past price fluctuation rate.[20] The calculations were conducted based on "R-language", which is known as the statistical language where many kinds of math and statistics formula are programmed.[7] The test concluded that that it is possible to determine whether they are in the same population or not. Statistical significance was assessed by using 95% confidence intervals and P< 0.05 was considered significant.

Relative frequency distribution for price frequency rate from Opening price to Closing price on the date 1 day to 3 days before and date of occurrence for EMP 2.0 was calculated, and significant difference was verified. The test was conducted for price fluctuations rate after 1 day to 3 days from EMP 2.0 occurrence to confirm whether there was a significant difference.

Normal distribution and homogeneity of variance were checked, and logarithmic transformations were made for all variables, if needed. Data was evaluated for normality against a normal distribution by using the *Kolmogorov-Smirnov test.* It was judged whether it was normal distribution or not. If the result was normal distribution, it was verified using the *F-test,* whether distribution of the data of EMP 2.0 and price fluctuations rate 1 day to 3 days before were the same or not. And about the average of the both, two-sided paired *t-test* in the case of equal variance and *Welch-test* in the case of nonparametric variant were determined. Then, as a result of this procedure of analysis and calculation, it was judged whether they were staying in the same population or not. In case the *Kolmogorov-Smirnov test* was non-normal distribution, the nonparametric variant *Wilcoxon signed rank test* was used for statistical analysis. And these methods were applied to judge whether they were in the same population or not.[9]

Test divided into White and Black candlestick

The result of Para.2.4.1 was divided into White and Black candlestick of a Candlestick chart, and it was verified. The manner of verification is the same as that which was used in Para.2.4.1. It was investigated whether there was significant difference or not. Difference with P<0.05 was considered significant as well.

Test of trend composition ratio

The price of each market was corrected based on 5-day moving average referring Ehlers (2002).[6,2] According to Ehlers, correction manner of moving average, moving average during period 'n' delays with (n-1)/2 to original price. Therefore, '2 days'

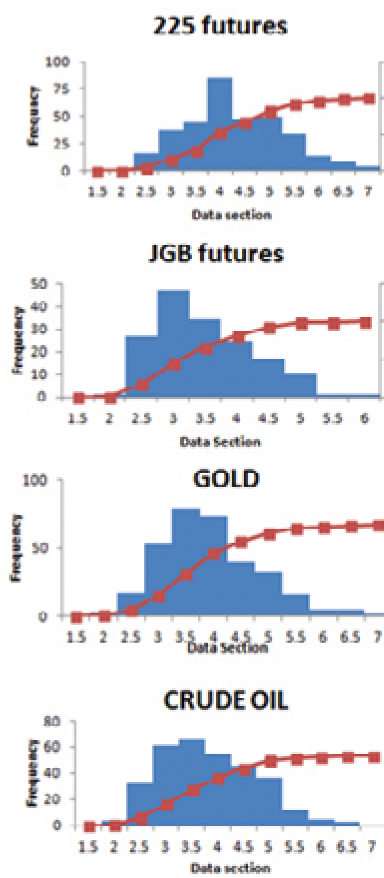
Figure 4. Histogram of EMP

225 futures	Price	EMP
Min	14030	2.07
Max	20840	8.00
Avg	17625	4.08
σ	2112	1.00
Data Quantity	342	

JGB futures	Price	EMP
Min	145.95	1.83
Max	148.34	7.20
Avg	147.49	3.70
σ	0.49	0.89
Data Quantity	163	

GOLD	Price	EMP
Min	1085.5	1.83
Max	1339.2	7.20
Avg	1201.4	3.70
σ	60.0	0.89
Data Quantity	324	

CRUDE OIL	Price	EMP
Min	38.24	1.78
Max	105.34	6.36
Avg	64.81	3.59
σ	19.02	0.92
Data Quantity	322	



*Red line is accumulated percentage. Blue is EMP frequency.
* Data from QUICK and Bloomberg.

was corrected for 5-day moving average. Based on the following definitions, trend was verified seeing price transition.

- UP: Price of the day is higher than that of the day before previous day, and lower than that of the day after next day.
- DOWN: Price of the day is lower than that of the day before previous day, and higher than that of the day after next day.
- PEAK OUT: Price of the day is higher than that of the day before previous day, and higher than that of the day after next day.
- BOTTOM UP: Price of the day is lower than that of the day before previous day, and lower than that of the day after next day.

In these four phrases, significant difference in statistics was verified for occurrence ratio and whole ratio of EMP 2.0 in the case of UP, DOWN, PEAK OUT and BOTTOM UP for 5-day moving average. (Manner of verification: R '*prop test*'),[7] and the price fluctuations rate of the day was divided into White candle and Black candle. 'Test of Equal or Given Procedure' was conducted to confirm in which cases of Black candle and White candle of 5-day moving average there were significant differences. These results of all four markets are shown in Table 11, and specific statistical test results are shown in each market paragraph below.

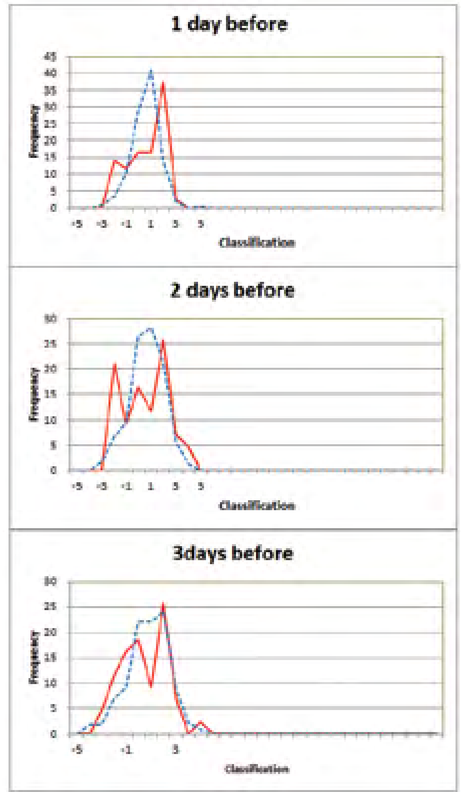
Results

Nikkei 225 futures

The analysis results for Nikkei 225 futures are mentioned below.

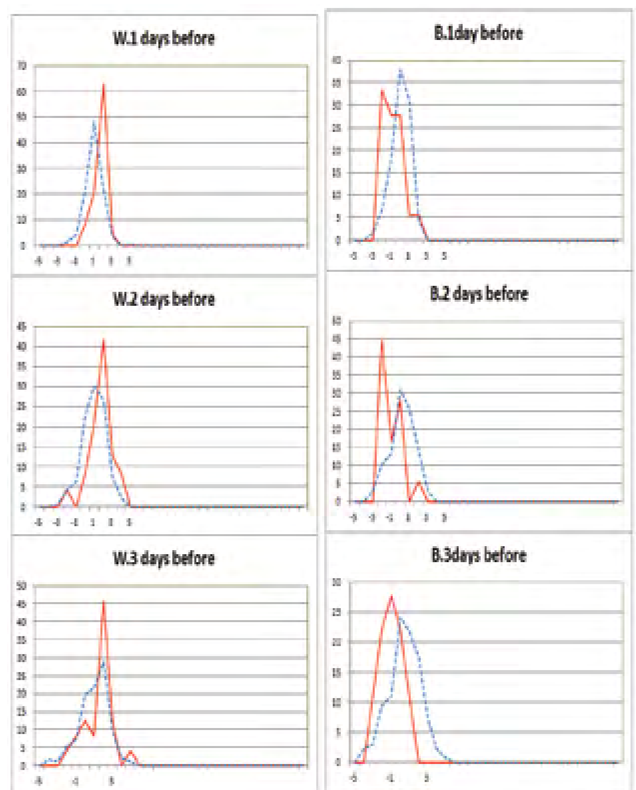
1. Figure 5 shows the EMP 2.0 frequency ratio and price fluctuations ratio distribution. According to Table 1, for the result of this statistical test, there was no significant difference in any case (1 day before, 2 days before, and 3 days before). However significant difference was found, as shown on price fluctuations rate distribution (Figure 6), in division into White candle day and Black candle day on 1 day before, 2 days before, and 3 days before. (Table 2)
2. Table 3 shows the verification result between price fluctuations rate after 1 day, 2 days, and 3 days for White candle day and Black candle day on which EMP 2.0 occurred. It was found that there was significant difference on the White candle day for 1 day, 2 days, and 3 days before. Then, it was also found that there were significant difference on the Black candle day for 1 day before and 2 days before. (3 days before was the exception.)
3. Table 11 shows the investigation result for EMP 2.0 and all trend ratio of price fluctuations rate. For the four phases UP, DOWN, PEAK OUT and BOTTOM UP of 5-day moving average, the frequency of EMP 2.0 occurrence and all of the ratio were investigated. As a result, although EMP 2.0 did not have a significant difference in all price fluctuations rate, EMP 2.0 tended to occur if 5-day moving average was in the case of significant difference "UP" on White candle day and Black candle day. And it was also found that EMP 2.0 tended to occur if 5-day moving average was in the case of "DOWN" on Black candle day.

Figure 5. Nikkei 225 futures, EMP 2.0 frequency distribution, and price fluctuations ratio distribution



*Red: EMP 2.0 Frequency ratio distribution
*Blue: All price fluctuations ratio distribution

Figure 6. Nikkei 225 futures, EMP 2.0 White and Black candle distribution



*Red: EMP 2.0 Frequency ratio distribution
*Blue: All price fluctuations ratio distribution

Table 1. Nikkei 225 futures, null hypothesis test

Kolmogorov–Smirnov test

225f	EMP2.0		All	
x days before	p-value	result	p-value	result
1 day	0.808	nomal distribution	0.281	nomal distribution
2 days	0.745	nomal distribution	0.174	nomal distribution
3 days	0.757	nomal distribution	0.306	nomal distribution

F test

x days before	p-value	result
1 day	0.011	Non-Equally Distribution
2 days	0.003	Non-Equally Distribution
3 days	0.000	Non-Equally Distribution

Welch-test summary

x days before	p-value	result
1 day	0.503	Same Population
2 days	0.994	Same Population
3 days	1.000	Same Population

Table 2. Nikkei 225 futures, Up (White candle) and Down (Black candle) test

Kolmogorov–Smirnov test

225f White candle	EMP2.0		All		Ftest		Ttest	
x days before	p-value	result	p-value	result	p-value	result	p-value	result
1 day	0.153	nomal distribution	0.245	nomal distribution	0.330	Equally Distribution	0.017	Non Same Population
2 days	0.545	nomal distribution	0.576	nomal distribution	0.674	Equally Distribution	0.001	Non Same Population
3 days	0.217	nomal distribution	0.533	nomal distribution	0.296	Equally Distribution	0.001	Non Same Population

225f Black candle	EMP2.0		All		Ftest		Ttest	
x days before	p-value	result	p-value	result	p-value	result	p-value	result
1 day	0.142	nomal distribution	0.623	nomal distribution	0.929	Equally Distribution	0.004	Non Same Population
2 days	0.074	nomal distribution	0.389	nomal distribution	0.334	Equally Distribution	0.003	Non Same Population
3 days	0.623	nomal distribution	0.623	nomal distribution	1.000	Equally Distribution	0.000	Non Same Population

Table 3. Nikkei 225 futures, test of 1-3 days after EMP 2.0 occurrences

Kolmogorov–Smirnov test

225f White candle	EMP2.0		All		Ftest		Ttest	
x days later	p-value	result	p-value	result	p-value	result	p-value	result
1 day	0.077	nomal distribution	0.290	nomal distribution	0.400	Equally Distribution	0.003	Non Same Population
2 days	0.274	nomal distribution	0.320	nomal distribution	0.867	Equally Distribution	0.001	Non Same Population
3 days	0.241	nomal distribution	0.693	nomal distribution	0.641	Equally Distribution	0.000	Non Same Population

225f Black candle	EMP2.0		All		Ftest		Ttest	
x days later	p-value	result	p-value	result	p-value	result	p-value	result
1 day	0.429	nomal distribution	0.193	nomal distribution	0.639	Equally Distribution	0.002	Non Same Population
2 days	0.464	nomal distribution	0.570	nomal distribution	0.946	Equally Distribution	0.000	Non Same Population
3 days	0.136	nomal distribution	0.499	nomal distribution	0.629	Equally Distribution	0.629	Same Population

Table 4. Nikkei 225 futures, trend composition test of equal or given proportions

225f	p value	result	White Candle day	p value	result	Black Candle day	p value	result
Up	0.481	not significantly different	Up	0.036	significantly different	Up	0.017	significantly different
Down	0.665	not significantly different	Down	0.064	not significantly different	Down	0.042	significantly different
Peak out	0.050	not significantly different	Peak out	0.274	not significantly different	Peak out	0.532	not significantly different
Bottom up	0.207	not significantly different	Bottom up	0.811	not significantly different	Bottom up	0.112	not significantly different

JGB futures

Analysis results for JGB futures are mentioned below.

1. EMP 2.0 frequency ratio and price fluctuations rate 1 day to 3 days before were in the same population, and there was no significant difference. Figure 7 shows the graph for EMP 2.0 and the price fluctuations rate on the previous day (and this is an example of the same group), and the red-line peak is not obvious and unstable.
2. Even if EMP 2.0 occurrence days are divided into White candle days and Black candle days, EMP 2.0 and price fluctuations rate were in the same group, and there was no significant difference.
3. Table 6 shows the investigation result for EMP 2.0 and the trend ratio of price fluctuations rate. EMP 2.0 tended to occur if the 5-day moving average was in the case of "UP" and "DOWN" on Black candle day.

Table 5. JGB futures, null hypothesis test

Kolmogorov-Smirnov test

JGBf	EMP2.0		All	
x days before	p-value	result	p-value	result
1 day	0.835	nomal distribution	0.577	nomal distribution
2 days	0.994	nomal distribution	0.349	nomal distribution
3 days	0.333	nomal distribution	0.787	nomal distribution

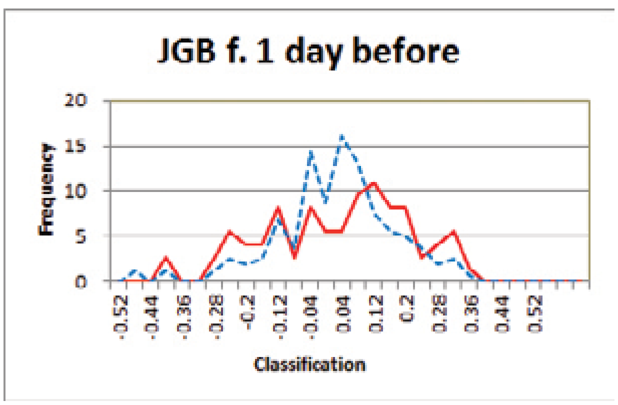
F test

x days before	p-value	result
1 day	0.017	Non-Equally Distribution
2 days	0.032	Non-Equally Distribution
3 days	0.002	Non-Equally Distribution

Welch-test summary

x days before	p-value	result
1 day	0.983	Same Population
2 days	0.984	Same Population
3 days	1.000	Same Population

Figure 7. JGB futures, EMP 2.0 1 day before



*Red: EMP 2.0 Frequency ratio distribution
*Blue: All price fluctuations ratio distribution

Table 6. JGB futures, trend composition test of equal or given proportions

JGBf	p value	result	White Candle day	p value	result	Black Candle day	p value	result
Up	0.804	not significantly different	Up	0.051	not significantly different	Up	0.002	significantly different
Down	0.806	not significantly different	Down	0.289	not significantly different	Down	0.024	significantly different
Peak out	0.245	not significantly different	Peak out	0.995	not significantly different	Peak out	0.594	not significantly different
Bottom up	0.320	not significantly different	Bottom up	0.301	not significantly different	Bottom up	0.081	not significantly different

Gold

Analysis results for Gold futures are mentioned below.

1. According to investigation for EMP 2.0 and price fluctuations rate in Table 7, as a result of the *Wilcoxon test*, there was significant difference on EMP 2.0 and price fluctuations rate 2 days before. However, Figure 8 shows significant difference was not found due to unstable peak of EMP 2.0, as shown on the red line in Figure 8.
2. There was no significant difference, even if EMP 2.0 and price fluctuations rate were divided into White candle day and Black candle day.
3. On the trend composition ratio (Table 8), although there was no significant difference for EMP 2.0 on the four cases of all price fluctuations rate, it was found that there was significant difference in the case of "UP" of 5-day moving average on EMP 2.0 White candle day and EMP 2.0 Black candle day.

Table 7. Gold null hypothesis test

Kolmogorov–Smirnov test

GOLD	EMP2.0		All	
x days before	p-value	result	p-value	result
1 day	0.325	nomal distribution	0.189	nomal distribution
2 days	0.551	nomal distribution	0.037	non-nomal distribution
3 days	0.487	nomal distribution	0.546	nomal distribution

F test

x days before	p-value	result
1 day	0.026	Non-Equally Distribution
3 days	0.017	Non-Equally Distribution

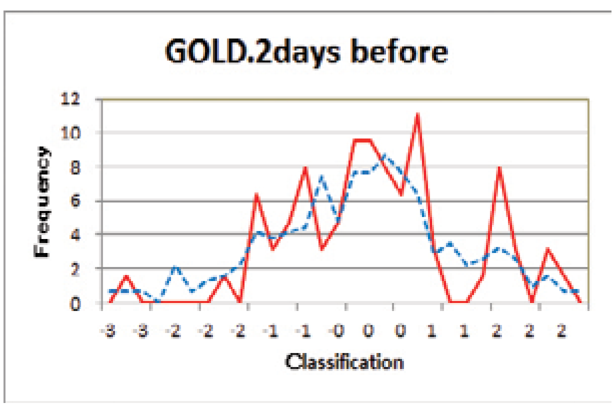
Wilcoxon(U)-test summary

x days before	p-value	result
2 days	0.045	Non Same Population

Welch-test summary

x days before	p-value	result
1 day	0.991	Same Population
3 days	1.000	Same Population

Figure 8. Gold, EMP 2.0 2 days before



*Red: EMP 2.0 Frequency ratio distribution
*Blue: All price fluctuations ratio distribution

Table 8. Gold, trend composition test of equal or given proportions

Gold	p value	result	White Candle day	p value	result	Black Candle day	p value	result
Up	0.827	not significantly different	Up	0.000	significantly different	Up	0.000	significantly different
Down	1.000	not significantly different	Down	0.185	not significantly different	Down	0.916	not significantly different
Peak out	1.000	not significantly different	Peak out	1.000	not significantly different	Peak out	0.931	not significantly different
Bottom up	0.681	not significantly different	Bottom up	0.163	not significantly different	Bottom up	0.811	not significantly different

Crude Oil

Analysis results for Crude Oil futures are mentioned below.

1. According to the investigation for EMP 2.0 and price fluctuations rate, frequency ratio of EMP 2.0 and distribution for price fluctuations rate 1 day before had significant difference on Table 9. However, significant difference was not found due to unstable peak of EMP 2.0 as shown on the red line in Figure 9.
2. There was no significant difference, even if EMP 2.0 and price fluctuations rate were divided into White candle day and Black candle day.
3. According to test for result ratio in Table 9, there was significant difference for EMP 2.0 in the case of "DOWN" of 5-day moving average on Black candle day.

Table 9. Crude oil, null hypothesis test

Kolmogorov–Smirnov test

CRUDE OIL	EMP2.0		All	
x days before	p-value	result	p-value	result
1 day	0.420	nomal distribution	0.688	nomal distribution
2 days	0.747	nomal distribution	0.045	non-nomal distribution
3 days	0.922	nomal distribution	0.520	nomal distribution

F test

x days before	p-value	result
1 day	0.061	Equally Distribution
3 days	0.004	Non-Equally Distribution

Wilcoxon(U)-test summary

x days before	p-value	result
2 days	0.122	Same Population

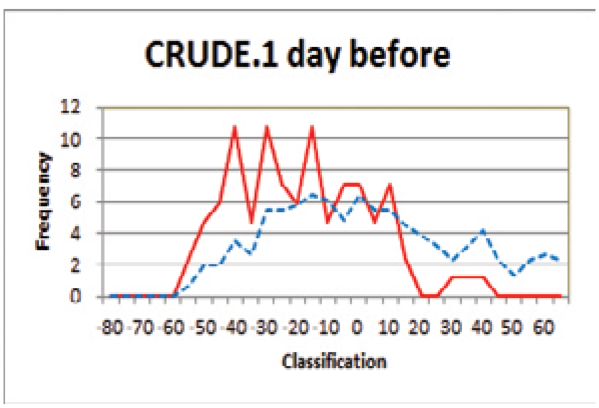
T-test summary

x days before	p-value	result
1 day	0.000	Non Same Population

Welch-test summary

x days before	p-value	result
3 days	0.991	Same Population

Figure 9. Crude oil, EMP2.0 1 day before



*Red: EMP 2.0 Frequency ratio distribution
*Blue: All price fluctuations ratio distribution

Table 10. Crude oil, trend composition test of equal or given proportions

Crude Oil	p value	result	White Candle day	p value	result	Black Candle day	p value	result
Up	0.042	significantly different	Up	0.275	not significantly different	Up	0.216	not significantly different
Down	0.046	significantly different	Down	0.202	not significantly different	Down	0.000	significantly different
Peak out	0.766	not significantly different	Peak out	1.000	not significantly different	Peak out	0.930	not significantly different
Bottom up	0.630	not significantly different	Bottom up	0.650	not significantly different	Bottom up	0.788	not significantly different

Refer to Table 11 about Trend composition ratio of EMP 2.0 and price fluctuations rate in each market.

Table 11. All trend composition ratio of EMP 2.0 and price fluctuations rate

225 futures	All		White candle		Black candle	
Trend	EMP2.0 ratio(%)	All ratio(%)	EMP2.0 ratio(%)	All ratio(%)	EMP2.0 ratio(%)	All ratio(%)
UP	52.4	50.5	75.0	50.5	17.6	50.5
DOWN	21.4	22.4	4.2	22.4	47.1	22.4
PEAK OUT	4.8	14.4	4.2	14.4	5.9	14.4
BOTTOM UP	21.4	12.7	16.7	12.7	29.4	12.7
計	100	100	100.0	100.0	100.0	100.0

JGB futures	All		White candle		Black candle	
Trend	EMP2.0 ratio(%)	All ratio(%)	EMP2.0 ratio(%)	All ratio(%)	EMP2.0 ratio(%)	All ratio(%)
UP	42.9	46.5	65.8	46.5	15.6	46.5
DOWN	27.1	22.6	13.2	22.6	43.8	22.6
PEAK OUT	11.4	14.8	13.2	14.8	9.4	14.8
BOTTOM UP	18.6	16.1	7.9	16.1	31.3	16.1
計	100	100	100.0	100.0	100.0	100.0

GOLD	All		White candle		Black candle	
Trend	EMP2.0 ratio(%)	All ratio(%)	EMP2.0 ratio(%)	All ratio(%)	EMP2.0 ratio(%)	All ratio(%)
UP	25.0	27.4	37.0	27.4	12.0	27.4
DOWN	50.0	47.6	33.3	47.6	68.0	47.6
PEAK OUT	11.5	12.1	14.8	12.1	8.0	12.1
BOTTOM UP	13.5	12.9	14.8	12.9	12.0	12.9
計	100	100	100.0	100.0	100.0	100.0

CRUDE OIL	All		White candle		Black candle	
Trend	EMP2.0 ratio(%)	All ratio(%)	EMP2.0 ratio(%)	All ratio(%)	EMP2.0 ratio(%)	All ratio(%)
UP	20.5	21.0	37.0	27.4	12.0	27.4
DOWN	49.4	51.8	33.3	47.6	68.0	47.6
PEAK OUT	12.0	13.4	14.8	12.1	8.0	12.1
BOTTOM UP	18.1	13.8	14.8	12.9	12.0	12.9
計	100	100	100.0	100.0	100.0	100.0

Discussion

Nikkei 225 futures

Relationship between EMP 2.0 and price fluctuations rate

White candle day: As shown on W.1, W.2 and W.3 of Figure 6, EMP (red line) stayed on right side of price fluctuations rate (blue-chain-line). It means that "UP" tends to happen because EMP 2.0 often occurs due to increasing of price fluctuations rate on previous date to 3 days before on White candle day. So it can be concluded that Trend day tends to occur after 1 to 3 days from the date when the White candle of price fluctuations rate is observed.

Black candle day: As shown on B.1, B.2 and B.3 of Figure 6, EMP (red line) stayed on left side of price fluctuations rate (blue-chain-line). It means that "DOWN" tends to happen because EMP 2.0 often occurs due to decreasing of price fluctuations rate on previous date to 3 days before on Black candle day. So it can be concluded that Trend day tends to occur after 1 to 3 days from the date when Black candle of price fluctuations rate is observed.

On the Trend day on which the market moves in one direction, earnings can be obtained in high possibility on day trading. Being able to forecast the occurrence of Trend Day has a big benefit, in that preparation for trading can be done in advance, and it can be utilized as the signal to prepare to compete in the market.

In this test, an obvious trend could not be observed in cases when EMP 2.0 tended to occur a few days from the date that either a White or Black candle price fluctuation rate was observed. If a trend is obvious, the value of EMP 2.0 will increase as the signal. In this thesis, whether the probability of an EMP 2.0's occurrence would increase or decrease depending on the subsequent price fluctuation rate was not considered, but it is thought that such research may enhance the signal value.

About use of the results for trading purposes

White candle day: The result that price fluctuation rate tends to occur 1 day to 3 days after the EMP 2.0 occurrence date on which price fluctuations rate increased suggests one should take a position on the White candle day during the few days after EMP 2.0 happens. (Although on the White candle day, there was a statistically significant difference 2 days after EMP 2.0 occurrence, it was judged that it was not a useful indication because EMP 2.0 did not have stable peak as seen in the graph.) Specifically, it is suggested that the position be held in the case of the condition under long position and EMP 2.0 occurrence, and the position must be closed in the case of the condition under short position and EMP 2.0 occurrence.

Black candle day: According to the result that price fluctuation rate tends to occur 1 day to 2 days after the EMP 2.0 occurrence date on which price fluctuations rate decreased, the example for making a position after EMP 2.0 occurrence on the Black candle day is to close on long position and to hold on short position. This is a short-term trade (a few days), so big earnings are not expected. However, it is valuable because loss and disadvantage can be avoided. It might be an essential indication for prop traders and day traders.

5-day moving average and using method of EMP 2.0 for 'Long and Short'

It is difficult to use as an indicator because Trend Day tends to occur in both White and Black candle days, although EMP 2.0 tends to occur in the case of an increasing 5-day moving average. This is because it cannot be judged which position, 'Long or Short', is better even if Trend Day tends to occur. So, trading-judgment is required to forecast initial range movement. According to the result that EMP 2.0 on Black candle day tends to occur if the 5-day moving average was decreasing, we must prepare for Trend Day on the Black candle day when the 5-day moving average decreases, and it can be said that it may be used for a short position. It must be noted that theoretical loss is unlimited for unexpected rising in a short position. However it can be expected as risk avoidance if Trend Day can be forecasted on "DOWN" in advance.

Summary for Nikkei 225 futures

The result shown above suggests that EMP 2.0 is useful for Nikkei 225 futures. Nikkei 225 futures are suitable for market profile because the market where price formation occurs is straightforward on the day-time, and the volume is sufficiently liquid. It is considered as the cause of the significant difference that Trend Day could be seen clearly because it was in "UP" due to quantitative and qualitative monetary easing during the testing of this thesis.

JGB futures

Relationship between EMP 2.0 and price fluctuations rate

There was no significant difference for EMP 2.0 frequency and price fluctuation rate 1 day to 3 days before on the whole day, White/Black candle day. As shown in Figure 7, the peak of EMP 2.0 (red line) was unstable, and the clear peak could not be found. Therefore it was hardly judged that EMP 2.0 could be used as an indicator for this section.

5-day moving average and using method of EMP 2.0 for 'Long and Short'

In the test for trend composition, it was found that EMP 2.0 tended to occur on the Black candle day of both for "UP" and "DOWN". According to this finding, it is suggested that we must prepare for Trend Day for Black candle day in both cases for increasing and decreasing for the 5-day moving average. However, the surrounding condition must be noted carefully because a significant difference beteween EMP 2.0 and the price fluctuation rate for White/Black candle day was not verified.

Summary for JGB futures

For JGB futures, the significant difference was not found between EMP 2.0 frequency and the price fluctuations rate. This is probably due to being strongly affected with Treasury-buying by the Bank of Japan; in other words, it was influenced by quantitative and qualitative monetary easing. So, normal conditions of financial policy must be watched because the portfolio hedger is not working properly, and the market, which lacks a chance of trade may continue due to extreme decrease of treasury in the market. Actually, market profile during the period of this test, Normal Days often continued and occasionally big Trend Days tended to occur because of exogenous influences such as treasury auctions, purchases by the Bank of Japan, and so on. Although the market profile for the last half of 1990s and beginning of 2000s, which Kashiwagi [10] introduced, cannot be seen recently, it is worth analyzing in the viewpoint of EMP 2.0 if the record is available.

Gold

Relationship between EMP 2.0 and price fluctuations rate

Although significant difference was found between EMP 2.0 frequency and the price fluctuation rate 2 days before, it was judged that EMP 2.0 is not useful as an indicator because, as Figure 8 shows, EMP 2.0 (red line) has a plural peak. The plural peak was also found in the test of division into White/Black candle day, so it must be judged that EMP 2.0 is not useful as an indicator.

5-day moving average and using method of EMP 2.0 for 'Long and Short'

In the test for trend composition, it was found that EMP 2.0 tended to occur both on the White/Black candle day of "UP". However, the result is not useful information, and the surrounding condition must be noted more carefully to use it as trading indicator.

Summary for Gold

In the market of Gold futures, it was difficult to forecast Trend Day using the price fluctuation rate. This is a surprising result because Market Profile was generated in the commodity market. Probable causes are that 1980s-style pit trading does not exist now, and the gold market is used in many cases for speculation. The intraday data that was used in this thesis included several time ranges and areas, such as New York, London and GLOBEX; so, in further analysis, intraday data may have to be defined by time range and area to consider the influence of trades from the other times and areas. In this verification, although the unit was 0.5 dollars to avoid the market profile making blank cells due to price-skipping, further tests using the 0.1 dollar unit provided that the exchange will be conducted.

Crude Oil

Relationship between EMP 2.0 and price fluctuations rate

Although significant difference was found between EMP 2.0 occurrence and price fluctuations rate 1 day before, it was judged that EMP 2.0 is not useful as an indicator because, as Figure 9 shows, EMP 2.0 (red line) has several peaks, and the clear peak could not be found as shown on Table 10. The plural peak was also found in the test of division into White/Black candle day, so it must be judged that EMP 2.0 is not useful as indicator for this section.

5-day moving average and using method of EMP 2.0 for 'Long and Short'

In the test for trend composition, it was found that EMP 2.0 tended to occur on the White candle day of "UP". So we had better prepare for making the position on the "UP" of the 5-day moving average as a hold on long position and close on short position. Although it was found that EMP 2.0 tended to occur on both White/Black candle day in the case of "DOWN" of the 5-day moving average, using a combination as a day-trade indicator needed to be considered to judge the movement of IR due to difficulty in using it as an indicator for making a position. And, like Gold futures, it is difficult to use it as an indicator because there were plural peaks on both White/Black candle day for the price fluctuation rate. So, the surrounding condition must be noted carefully.

Summary for crude oil

The cause for there being no significant difference for EMP 2.0 in the Crude Oil market is that the market was volatile in the down phase during the testing period and, as shown in Figure 4, Trend Day frequently occurred. So, it needs to be verified again whether Trend Day really occurs with EMP 2.0. It is considered that EMP 2.0 is improper for forecasting Trend Day occurrence on the next day because there are fewer market participants who have outright position due to New York oil being the market for arbitrage transaction of commercial industry, spread transaction major, intraday data covers only 1/4 of 24 hours dealing. Therefore, new verification with different time range is required. Although in this thesis, the unit was 0.05 dollars, further analysis to make the market profile meet the provisions of the exchange with proper unit 0.01 dollars as correction will be conducted.

Problems and limit of present study

Using minute data can enhance the quality of analysis. However, only short-term data is available now, and drawing the chart for Market Profile is time-consuming, so long-term analysis is difficult to conduct in the same way by using Microsoft Office Excel. EMP 2.0 mentioned in this thesis needs to be handled in a sensitive manner because EMP value must change with different units, and the market-wise EMP definition may be required with transition of the market. Larger data than was used in this thesis are required to enhance the quality of analysis. Additionally, combining other technical information will help to enhance the quality of analysis by incorporating the advice of many experienced technical traders who have devoted a lifetime to developing their technical systems.

Suggestions for further study

According to analysis and verification for trend day definition with EMP 2.0, there was obvious differences for Nikkei 225 futures, and in White candle and Black candle with 3 days before until 2 days after occurrence of EMP 2.0. So it can be said that EMP 2.0 is a useful and suitable indication for Nikkei 225 futures. EMP 2.0 can be utilized in high accuracy. So, in the next thesis, verification for S&P 500, DJIA, and Nasdaq futures and individual stocks needs to be conducted. By the test of trend composition, both White and Black candle days' "UP" and "DOWN" phase tended to occur on Trend day. In "PEAK OUT" and "BOTTOM UP" phase, EMP 2.0 tended to be unrelated to the trend frequency.

Surprisingly, EMP 2.0 as the Trend day indicator is not useful for the commodity market in which the Market Profile was established. It is difficult to predict Trend Day occurrence for the Gold and Oil markets, even through using EMP 2.0. Reliability of Market Profile probably decreases in the Oil market, which is highly volatile and has frequent price variations, and it might be impossible to predict the future, even using intraday data of the market stimulated with GLOBEX. So, for further analysis and verification, time slot-wise investigation for GLOBEX and/ or drawing a Market Profile chart connecting each volume of historical data will be required. And, it also was found that EMP 2.0 was not useful for JGB futures.

Additionally, accuracy will be enhanced for the 'central-limit theorem' using increased numbers of the data.[3] Simultaneously, further investigation is also required to increase the number of the data where they were dismissed due to 0.05 difference of *p-value*. Although in this thesis, data verification was focused on using EMP 2.0 to predict Trend Day, EMP will be examined with actual trading in the next thesis as a future subject. EMP works like an oscillator, which has ability to correct. So, more accurate analysis will be able to be conducted with a combination of the EMP and other technical analysis, such as cycle analysis, as Murphy, who is authority on futures technology, suggested.[13]

Conclusion

In this thesis, we conclude the following three points as a result of current investigations and analysis.

First, EMP 2.0 is useful for Nikkei 225 futures. In the next thesis, S&P 500, DJIA, and Nasdaq futures will be verified with an increased number of the data using EMP. The condition of Trend Day frequency was verified by defining Trend Day using EMP. In Nikkei 225 futures market, the condition of Trend Day frequency was found through statistical differences divided into White and Black candle day and composition of trend test by a 5-day moving average.

Secondly, currently it is difficult to predict Trend Day occurrence for Gold futures and Crude Oil futures, probably because of high market volatility and easily varying price, and it needs further analysis. It was found that EMP was not a useful indicator for commodities, even though those markets are the origin of the Market Profile. EMP 2.0 seems to be applicable to stock futures index. It is different environment from 1980; there is no floor market and there are more speculators than commercial traders.

Thirdly, EMP 2.0 is not useful for JGB futures, and it required further analysis.

In the next thesis, the other markets will be tested with a larger volume of data using EMP, and this method will be conducted using actual trades.

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The Composite Index: A Divergence Analysis Study

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Abstract

Asset managers often use normalized oscillators such as Wells Wilder's Relative Strength Index (RSI)[1] and Gerald Appel's Moving Average Convergence/Divergence Oscillator (MACD)[2] to enhance their fundamental metrics. Normalized oscillators travel in a fixed range between zero and 100. The expectation is that these normalized oscillators will display a divergence away from the developing price trend in order to warn of an approaching trend reversal. However, a common problem in Global Equity Indexes is that the RSI oscillator frequently fails to show any divergence. As a result, there is no warning in long horizon trends of a major price reversal up or down.

This paper will demonstrate how imbedding a Momentum formula within the Relative Strength Index will significantly improve the trend reversal signal and timing characteristics of this oscillator. The method has benefits for shorter-horizon traders as well.

Introduction

Composite Index Oscillator

The Composite Index[3] oscillator was developed by Connie Brown under the guidance of Manny Stoller. The problem we faced several decades ago is still present today; the Relative Strength Index, as developed by Welles Wilder,[2] does not develop oscillator divergences against long-horizon price data. The failure to display divergence signals against price is costly for asset managers as major trend reversals can occur without any warning from this widely relied upon indicator.

The Market Technician Association's *Journal of Technical Analysis* (Winter 1993—Spring 1994; 42: p. 45) published The *Derivative Oscillator: A New Approach for an Old Problem* by Connie Brown.[4] This early work introduced a triple smoothed derivative of RSI plotted as a histogram. The formula imbedded a smoothed short 3-period RSI within a standard 14-period RSI as developed by Welles Wilder. The character of the *Derivative Oscillator* was found to provide less noise and more clearly defined amplitude signals to aid the development of Elliott Wave Principle[5] interpretations. The results found that the simple histogram was free ranged, and the first maximum extremes mapped with third-of-third wave positions. The divergence amplitude mapped to the fifth wave positions. This was repeatable. However, the conventional 14-period RSI did not display any divergence at similar pivot points.

From this work in 1991, Manny Stoller of Cantor Fitzgerald asked me to develop this concept further by imbedding other formulas into the oscillator in an effort to find a possible solution for the divergence problem we clearly observed within the RSI.

The Composite Index oscillator is the solution to this RSI divergence problem for asset managers and traders. The Composite Index against the RSI is tested with the long horizon price data of the German DAX, French CAC 40 Index, China Shanghai Composite Index, Dow Jones Industrial Average, 10-Year U.S. Government Bond Yields, and 10-Year Japanese Government Bonds.

Composite Index Formula

- The Composite Index formula is as follows:
- (Omega *TradeStation* format)[1:]
- Plot1(RSIMO9+RSI3,"Plot1");
- Plot2(average((plot1),13),"Plot2");
- Plot3(average((plot1),33),"Plot3");
- The function RSIMO9 is written; RSIMO9 = MOMENTUM(RSI(CLOSE,14),9)
- The second function is written RSI3=AVERAGE(RSI(CLOSE,3),3)

This paper excludes the moving averages in 'Plot2' and 'Plot3' so that the Composite Index formula, with the imbedded Momentum formula, can be studied in-depth against the conventional 14-period RSI oscillator. Momentum is a simple comparison. The imbedded 9-period Momentum in the Composite Index, is the comparison between the most recent 14-period RSI value to the RSI value from nine periods earlier. By imbedding Momentum into the RSI formula, it allows the RSI to have a free range travel and is not limited to the normalized range of zero to 100.

Methodology

Divergence Analysis

Divergence is determined by applying a linear regression test. A six-bar linear regression comparison is made between the Composite Index and RSI by the Market-Analyst[6] tool called 'Divergence (DIV)'. Table 1 shows how column 'A' will record the signal date when divergence is identified by Market-Analyst software. The settings have to be changed from the default comparison between the oscillator and the price data so that the comparison occurs between the Composite Index and RSI. (Figure 12)

Cell (D:7) in Table 1 records the number of indicator periods that are used for each linear regression test. Column D records a 'Buy' signal when the Composite Index has a positive divergence to RSI. A 'Sell' signal occurs when the Composite Index has a negative divergence to RSI.

Table 1. German DAX—Divergence Analysis Test Criteria

German DAX - 2 month Bar Chart

Signal Date	Price Range Prior Swing	Reversal Swing* Criteria Test (see below)	Linear Regression Divergence Signal (6 Bar LR)	Swing Price High/Low	# Bars Swing H/L Exceeded (> H/L3?)	Price Move After Signal	Percent Retrace Following Signal to prior Swing (>35.0 %?)	Divergence Signal Pass/Fail
3/29/2015	6,476	active	Sell	H- 11,920	active	-2582(active)	active	open
6/10/2007	5,962	passed	Sell	H- 8,151	H33	-4,562	76.50	passed
2/14/2003	-5947	passed	Buy	L- 2,188	H74	5,962	100.26	passed
6/7/1998	4326	passed	Sell	H- 6,217	H8	-542	35.66	passed
6/9/1990	1045	passed	Sell	H- 1,976	H9	-664	63.58	passed

* Swing Criteria Test: Bar= 4, Percent= 9.0, Calculate Using: High/Low

example: If start of swing is a high; 9% is calculated by High - (High x 0.9), if prior swing length = 100 at least $9 retracement.

Bar = 4 means criteria is true after 4 bar reversal minimum.

NOTE: From 1984 to 2015 the German DAX triggered five divergence signals in the two-month bar chart. Four signals were "Sell" signals and one was a "Buy" signal. One signal remains open, as the signal remains active in current markets. The four closed signals all had a "passed" result.

A six-bar linear regression setting is a minimum. The program will examine the 7th value and elongate the highlight box on the chart as long as the divergence continues.

When divergence between the Composite Index and RSI is identified, it would be undesirable if the signal should fall within a trending price swing. Price swings are drawn on the price data by using an analysis tool called the 'Percent Swing Overlay' (PCSC). Two conditions must be met before the trending swing can be reversed.

The first condition is when 'Bars= 3'. A swing reversal condition is 'True' only after a minimum three-bar reversal. In a two-month bar chart, a swing reversal can only occur after a six-month period that is a desirable holding period for most fund managers. Equity Indexes all required a three-bar reversal. U.S. Treasury Note Yields and Japanese Government Bonds required "Bars" to be set at '1', as the next test was found to be more important.

The second condition for a price swing reversal to occur is the retracement percentage minimum. When 'Percent' equals 9.0, as was used in all the equity indexes tested, it means if the start of the swing is a high; 9% is calculated by High – (High x 0.09). If the prior swing length equals $100 then there must be at least a $9 retracement to trigger a new swing. The swing is the blue and green line drawn through the price data in all figures connecting swing low to high or high to low. When the divergence signal between oscillators develops at a price low, Low + (Low x 0.09) is used for a 9% reversal. Column E will record the price high (H) or low (L) nearest the actual divergence signal. A divergence signal must occur within two bars of a new price swing. If the signal occurs later it is marked as a 'failed' signal.

Column "B" in Table 1 records the price range of the swing preceding the divergence signal that is used to calculate the retracement percentage.

As it is undesirable to have a divergence signal that immediately fails when prices break through the signal price, Column F was added called: '# Bars (after pivot) Swing H/L Exceeded. Cell (F:7) in Table 1 shows (> H/L3?). A tool in Market-Analyst 8 called 'Pivot Labels' will count how many bars forward will develop before that specific pivot high (H) or pivot low (L) is exceeded. A divergence signal will 'fail' in this test if the buy price is exceeded or the sell price is penetrated to the downside after three bars or less. Figure 1 is a two-month German DAX bar chart with Pivot Labels. Within Figure 1 a horizontal line has been drawn between the pivot label showing 'H44' on March 1, 2000, and the price high on July 1, 2007. This is an example to show how the pivot price was exceeded 44 bars later. Each swing will have a pivot label. If column F shows 'active', the price pivot has not been retraced or broken by the market.

Column G in all the tables will record the price move after the divergence signal. Column H will record the percentage retracement following the divergence signal as compared to the price range of the prior swing in Column B. Column G will be red, denoting a failure, if the percent retracement is less than 35.0%. The 35% value was consciously selected to be under the common Fibonacci retracement ratio of 38.2%. The last Column 'I' will show a 'failed' label if any of the divergence tests are found not to be true. When all the criteria has been met as described for columns C, F, and H, the label 'passed' will be found in the results column for the signal in Column I. Failed signals will also have comments on the bottom right of each table to clarify the tests that triggered a 'failed' result.

Results

These results summarize my findings of the divergence study. Each market tested will have a chart or charts to show the divergence signals extracted by Market-Analyst's linear regression formula over the dates in question. The charts are always followed by summarized supporting tables. This section only displays the results of the Composite Index study and the interpretation will be found in the next section, called "Discussion".

Figure 1. German DAX—Two-Month Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay (1984–2015)

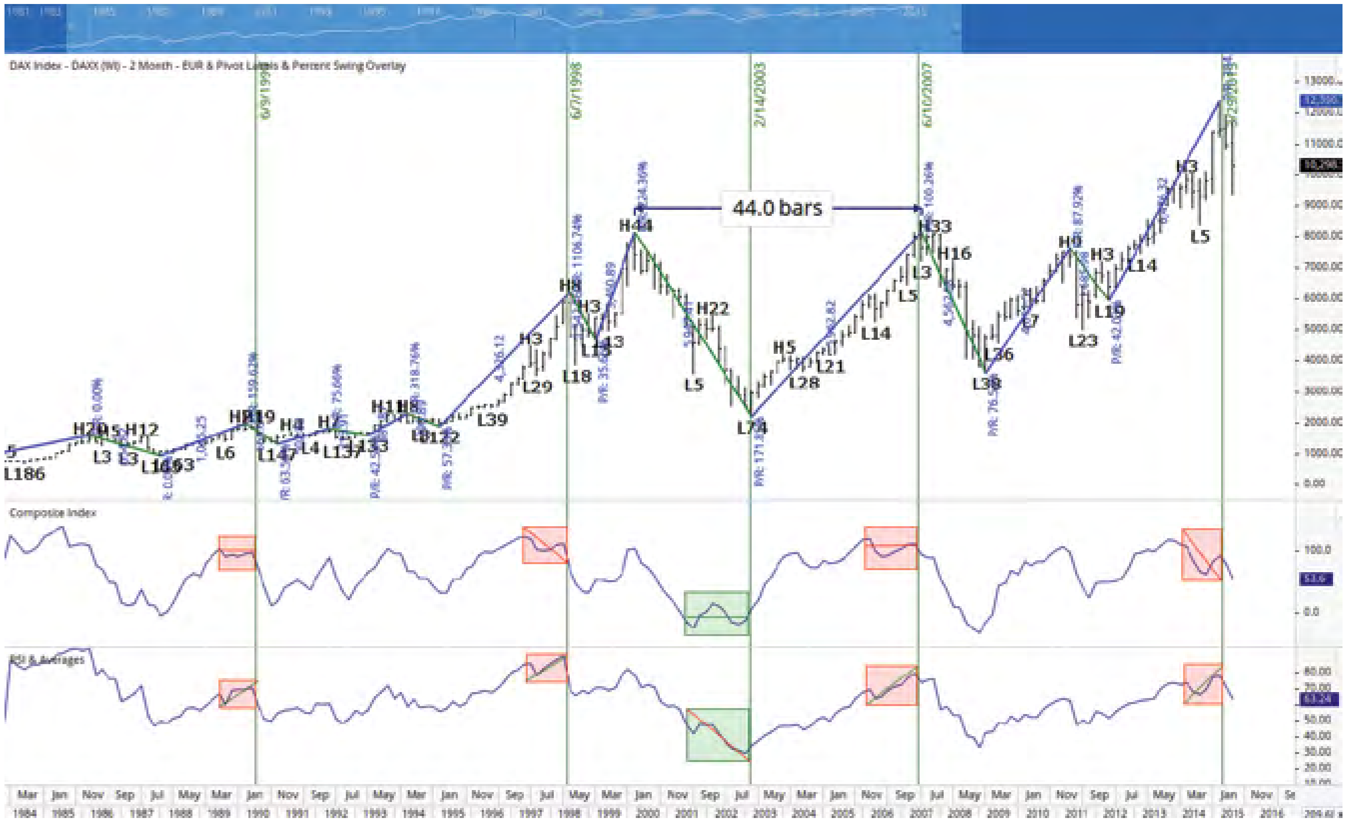


Figure 2. French CAC 40 Index—Two-Month Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay (1990–2015)

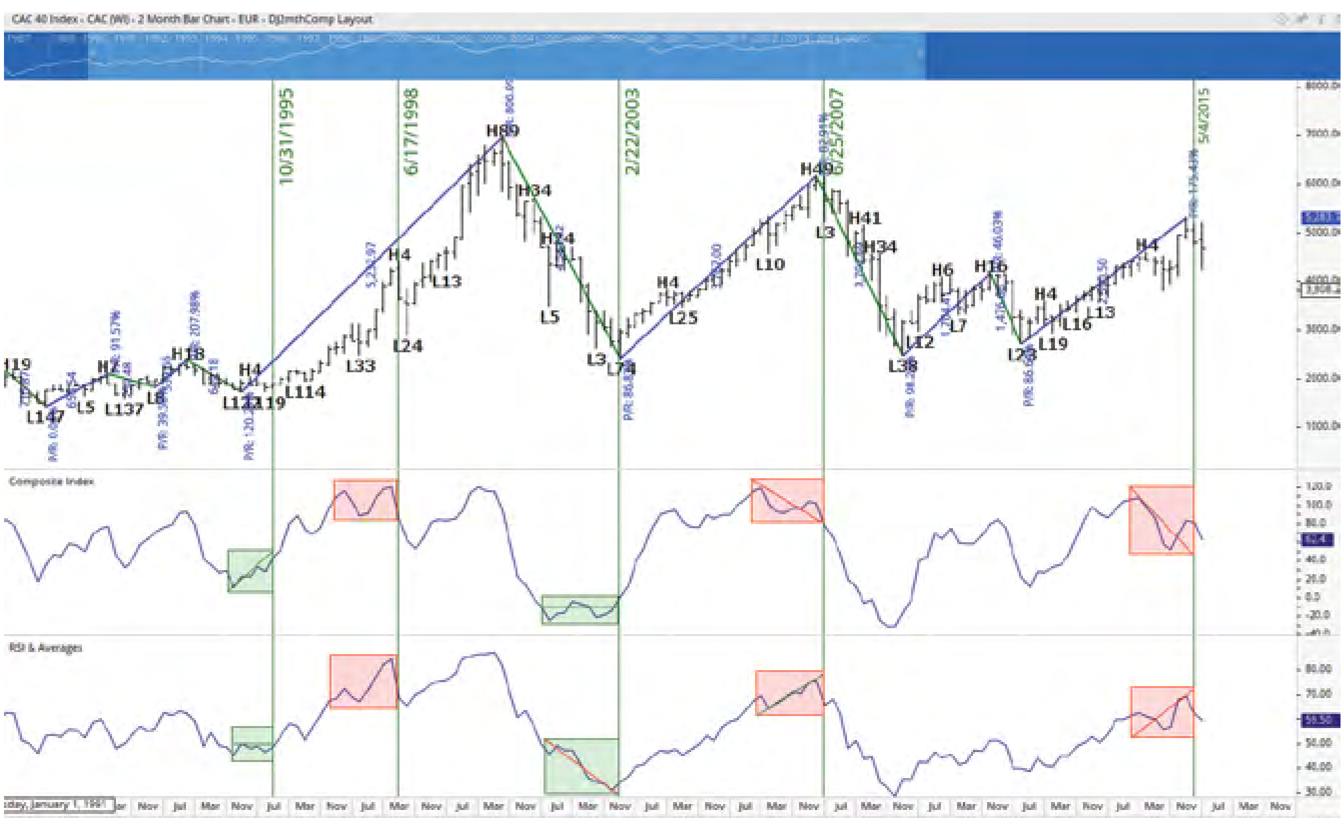


Table 2. F rench CAC 40 Index—Two-Month Bar Chart Divergence Signal Analysis

	A	B	C	D	E	F	G	H	I
21	French CAC 40 Index - 2 month Bar Chart								
22				Linear Regression	Swing	# Bars		Percent Retrace	
23	Signal Date	Price Range	Reversal Swing*	Divergence	Price	Swing H/L	Price Move	Following Signal	Divergence Signal
24		Prior Swing	Criteria Test	Signal	High/Low	Exceeded	After Signal	to prior Swing	Pass/Fail
25			(see below)	(6 Bar LR)		(> H/L3?)		(> 35.0 %?)	
26									
27	5/4/2015	2,590	active	Sell	H- 5,193	active	-963(active)	active	open
28	6/25/2007	3,767	passed	Sell	H- 6,168	H49	-3,702	98.29	passed
29	2/22/2003	-4543	passed	Buy	L- 2,401	H74	3,767	82.91	passed
30	6/17/1998	4326	failed**	Sell	H- 4.404	H4	-1,523	86.6 *	failed**
31	10/31/1995	-649	passed	Buy	H-1,976	L119 (active)	5232	806.09	passed
32									
33	* Swing Criteria Test: Bar= 3, Percent= 9.0, Calculate Using: High/Low						** divergence falls in the middle of long horizon swing		
34	example:	If start of swing is a high; 9% is calculated by							
35		High - (High x 0.9), if prior swing length = 100 at least $9 retracement.							
36		Bar = 3 means criteria is true after 3 bar reversal minimum.							
37									

NOTE: From 1990 to 2015 the French CAC 40 Index triggered five divergence signals in a two-month bar chart. Three signals were 'Sell' signals and two were 'Buy' signals. One signal remains open, as the signal remains active in current markets. Of the four closed signals, three passed and one failed because the divergence signal was triggered in the middle of a long horizon swing.Figure 3. China—Shanghai Composite Monthly Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay. (1995—2015)

Figure 3. China—Shanghai Composite Monthly Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay (1995—2015)

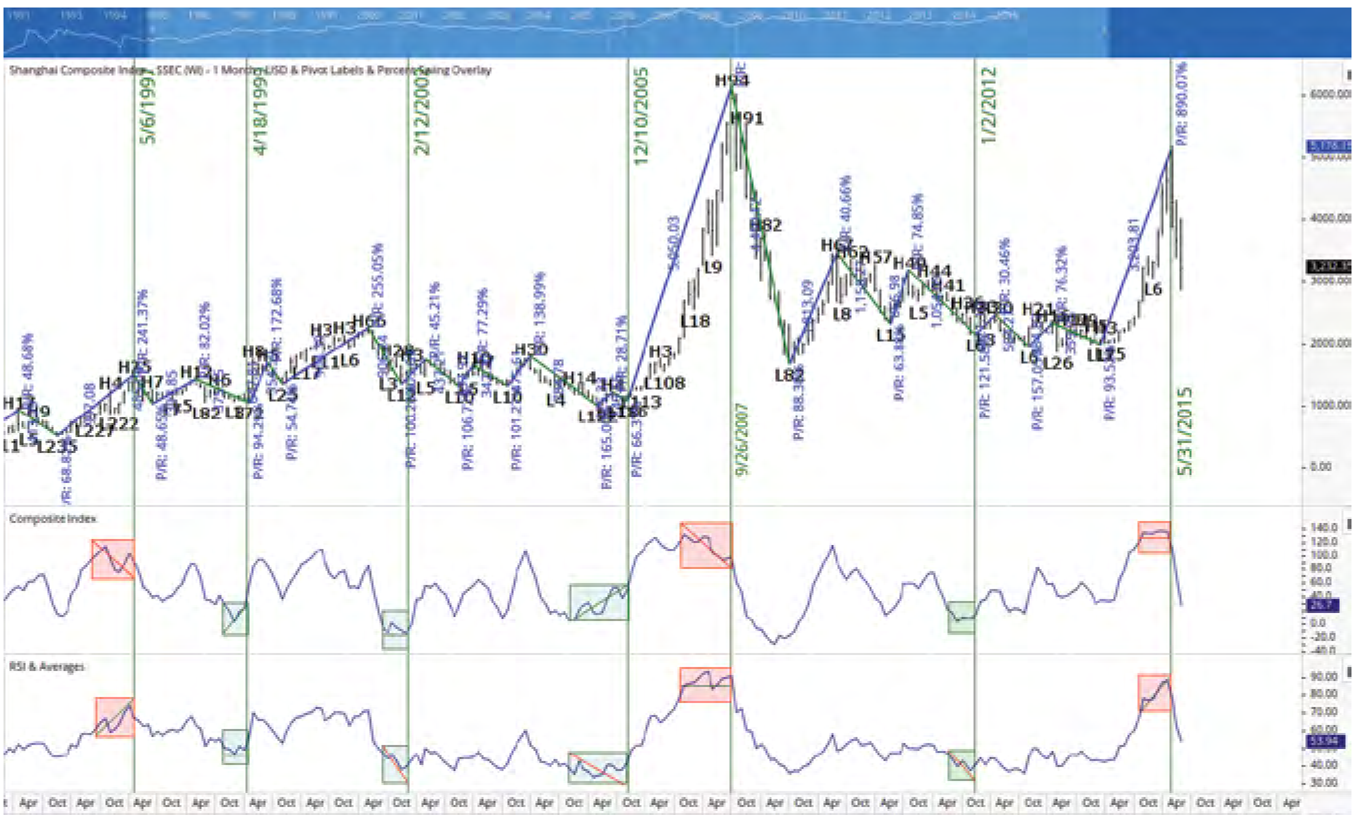


Table 3. China Shanghai Composite Index—Monthly Bar Chart Divergence Signal Analysis

China Shanghai Composite - 1 month Bar Chart

Signal Date	Price Range Prior Swing	Reversal Swing* Criteria Test (see below)	Linear Regression Divergence Signal (6 Bar LR)	Swing Price High/Low	# Bars Swing H/L Exceeded (> H/L3?)	Price Move After Signal	Percent Retrace Following Signal to prior Swing (> 35.0 %?)	Divergence Signal Pass/Fail
5/31/2015	3,203	active	Sell	H-4,986	active	-2136(active)	active	open
1/2/2012	-1,054	passed	Buy	L- 2,132	L6	317	30.46	failed**
9/26/2007	5,050	passed	Sell	H- 6,005	H94 (active)	-1,213	86.99	passed
12/10/2005	-784	passed	Buy	L- 1,074	L86	5,050	3376.82	passed
2/12/2002	-906	passed	Buy	L- 1,476	L12	409	45.2	passed
4/18/1999	-375	passed	Buy	L- 1,047	L72	1,197	319.24	passed
5/6/1997	997	passed	Sell	H- 1,510	H25	-485	48.65	passed

* Swing Criteria Test: Bar= 3, Percent= 9.0, Calculate Using: High/Low

example: If start of swing is a high; 9% is calculated by High - (High x 0.9), if prior swing length = 100 at least $9 retracement. Bar = 3 means criteria is true after 3 bar reversal minimum.

** decline failed to exceed the 35% or greater test

NOTE: From 1995 to 2015, the China Shanghai Composite Index triggered seven divergence signals in a monthly bar chart. Of the seven signals, four were 'Buy' signals and three were 'Sell' signals. The most recent 'Sell' signal remains open, as the signal remains active. Five divergence signals passed. One failed because the percentage retracement did not meet the trend retracement criteria of greater than 35%. The retracement was 30.46%. A monthly bar chart was used due to the limited historical data for this market.

Figure 4. Dow Jones Industrial Average—Two-Month Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay (1981–2015)

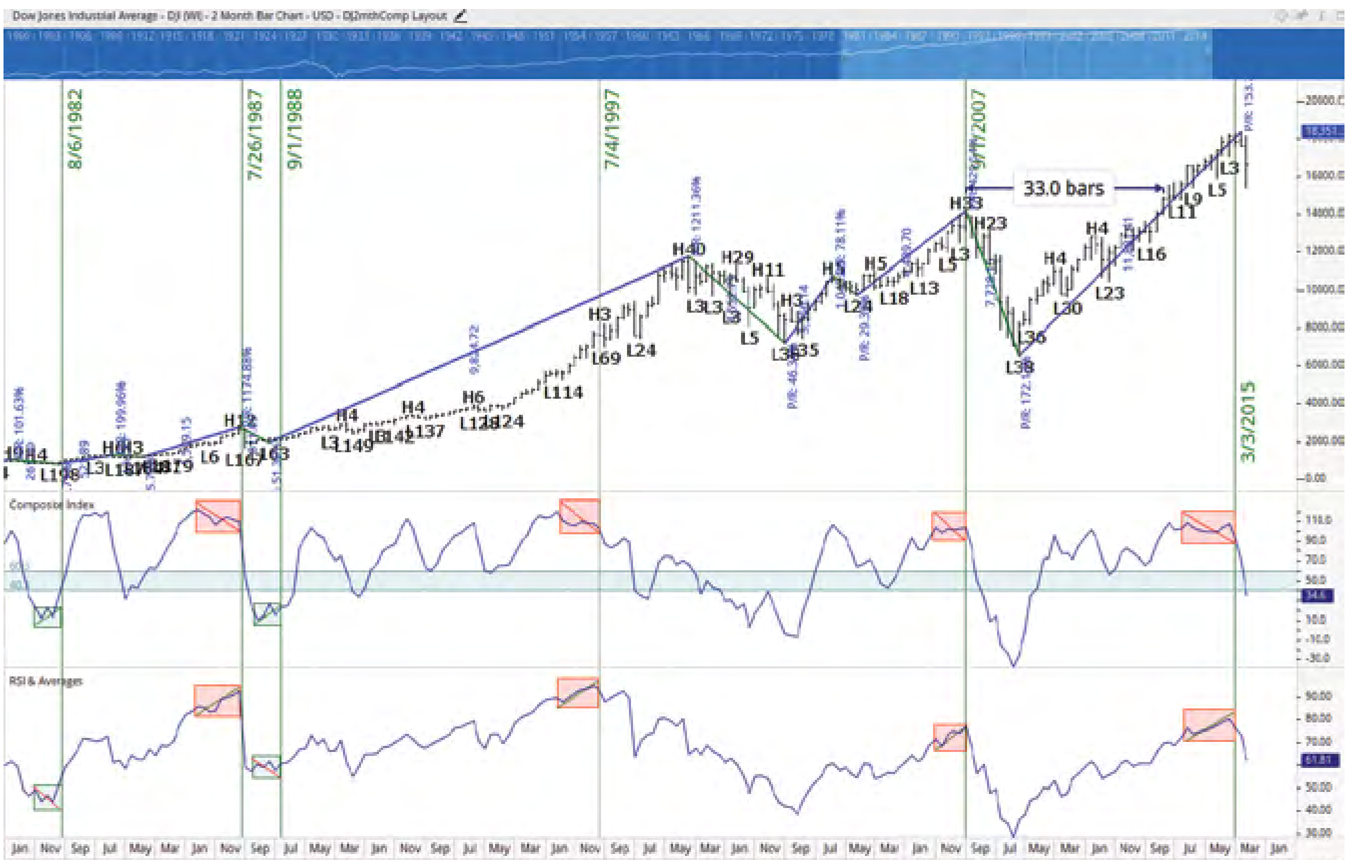


Figure 5. Dow Jones Industrial Average—Two-Month Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay (1951–1982)

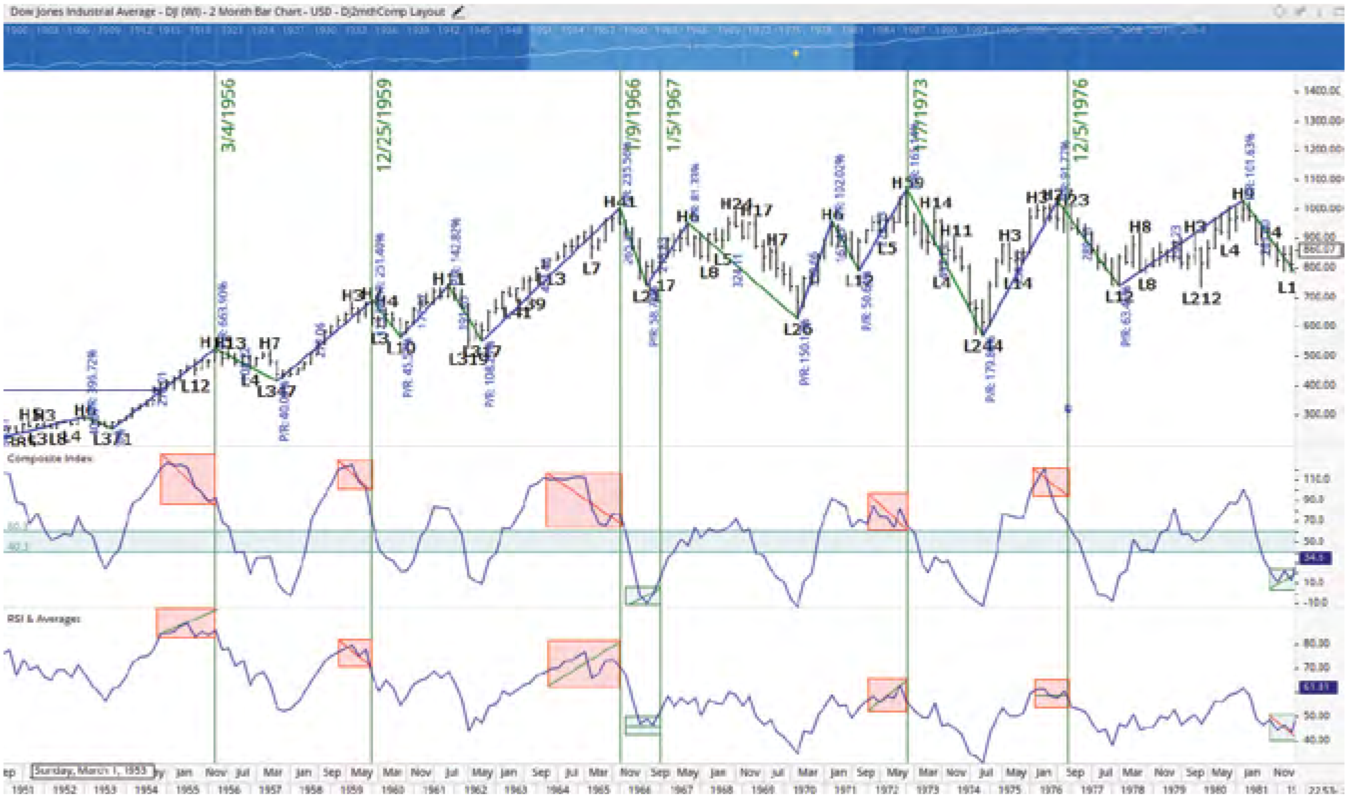


Figure 6. Dow Jones Industrial Average—Two-Month Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay (1919–1951)

Table 4. Dow Jones Industrial Average—Two-Month Bar Chart Divergence Signal Analysis

	A	B	C	D	E	F	G	H	I
59	**Dow Jones Industrial Avg - 2 month Bar Chart**								
60				Linear Regression	Swing	# Bars		Percent Retrace	
61	Signal Date	Price Range	Reversal Swing*	Divergence	Price	Swing H/L	Price Move	Following Signal	Divergence Signal
62		Prior Swing	Criteria Test	Signal	High/Low	Exceeded	After Signal	to prior Swing	Pass/Fail
63			(see below)	(6 Bar LR)		(> H/L3?)		(> 35.0 %?)	
64									
65	3/3/2015	11,881	active	Sell	H- 18,351	active	-2981(active)	active	open
66	9/1/2007	4,489	passed	Sell	H- 14,198	H33	-7,728	172.13	passed
67	7/4/1997	6374	failed**	Sell	H- 8,299	H3 +	-1,328	20.8	failed + **
68	9/1/1988	-811	passed	Buy	L- 1,996	L163 (active)	9,824	1211.4	passed
69	7/26/1987	1579	passed	Sell	H- 2,736	H12	-811	51.36	passed
70	8/6/1982	-761	passed	Buy	L- 888	L198(active)	521	199.9	passed
71	12/5/1976	456	passed	Sell	H- 1,006	H23	-289	63.45	passed
72	1/11/1973	276	passed	Sell	H- 1,067	H59	-497	179.8	passed
73	1/5/1967	-265	passed	Buy	L- 735	L21	87	81.33	passed
74	1/9/1966	41	passed	Sell	H- 1001	H41	142	55.68	passed
75	12/25/1959	272	passed	Sell	H- 688	H7	-123	45.6	passed
76	3/4/1956	270	passed	Sell	H- 524	H13	-108	26.41	failed
77	1/11/1948	-15	failed	Buy	L- 174	L8	29	63.65	failed 2**
78	5/13/1946	120	passed	Sell	H- 213	H23	-52	43.08	passed
79	2/10/1937	111	passed	Sell	H- 195	H52	-98	88.38	passed
80	5/31/1932	-345	passed	Buy	L- 40.6	L498 (active)	active	active	passed
81	9/1/1929	297	passed	no signal**	H- 386	H151	-	-	-
82	2/7/1923	41	passed	Sell	H- 105	H8	-27	46.99	passed
83	8/3/1921	55	passed	Buy	L- 66.8	L64	41	74.51	passed
84									
85	* Swing Criteria Test: Bar= 3, Percent= 9.0, Calculate Using: High/Low				no signal** Divergence is present between the Composite Index and RSI,				
86	example:	If start of swing is a high; 9% is calculated by			but the signal was filtered out due the the width of the signal				
87		High - (High x 0.9), if prior swing length = 100 at least $9 retracement.							
88		Bar = 4 means criteria is true after 4 bar reversal minimum.			+** Signal falls in the middle of a swing, failed Time test (H3) and				
89					failed the retracement percentage test				
90									
91					2** Signal falls in the middle of a Swing				

NOTE 1: From 1919 to 2015, the Dow Jones Industrial Average triggered 18 divergence signals in a two-month bar chart. Of the 18 signals, six were 'Buy' signals, and 12 were 'Sell' signals. The most recent 'Sell' signal remains open, as the signal remains active. Fourteen divergence signals passed. Three signals failed. One signal failed for multiple reasons. The signal on July 4, 1997, failed because it was triggered further than the two-bar minimum after a swing reversal. It also failed because the price high was exceeded three bars later when the criteria was set to a three-bar minimum. The sell signal led to a 20.8% decline and did not met the 35% retracement minimum of the previous swing. The signal on 1/11/1948 followed too late after the start of the new swing, though the signal did yield a 63.65% retracement of the prior swing.

NOTE 2: Because of the historic price high of September 1, 1929, this date was added to Table 4. Figure 6 shows a hand drawn divergence signal recording a divergence into this date, but a filter was established within the Composite Index of 40 to 60. This means any value in the linear regression that falls within this band is filtered out, and regression starts a new count. Therefore, a result of 'no signal' is in Column D for this date because the Composite falls to this filtered range. This was done to filter any signal that had an exceptionally long divergence pattern, and the filter acted as a time variable within the regression test. This filter was only applied to the DJIA.Figure 7. 10-Year U.S. Treasury Note Yields—Two-Month Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay. (1990—2015)

Figure 7. 10-Year U.S. Treasury Note Yields—Two-Month Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay (1990–2015)

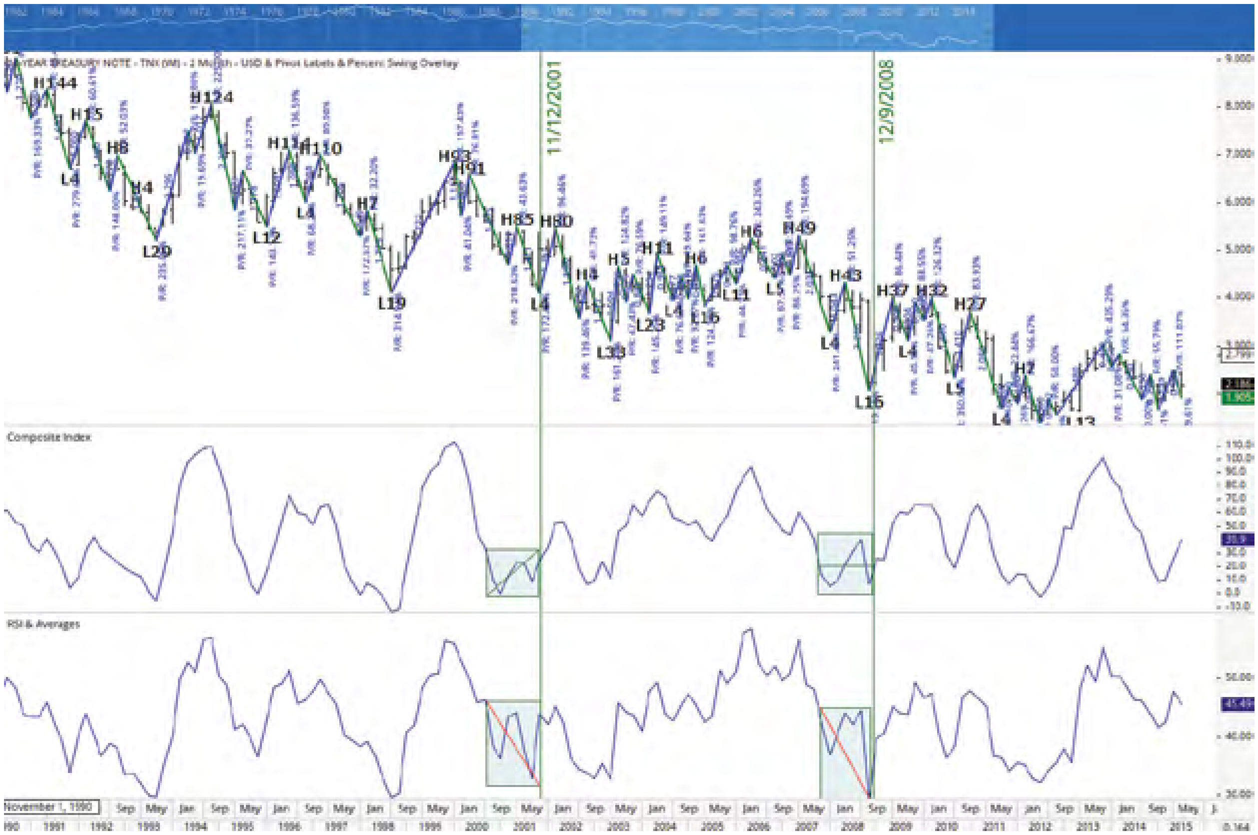


Figure 8. 10-Year U.S. Treasury Note Yields—Two-month Bar Chart with Linear Regression Divergences, Pivot Labels, and Percent Swing Overlay (1966–1990)

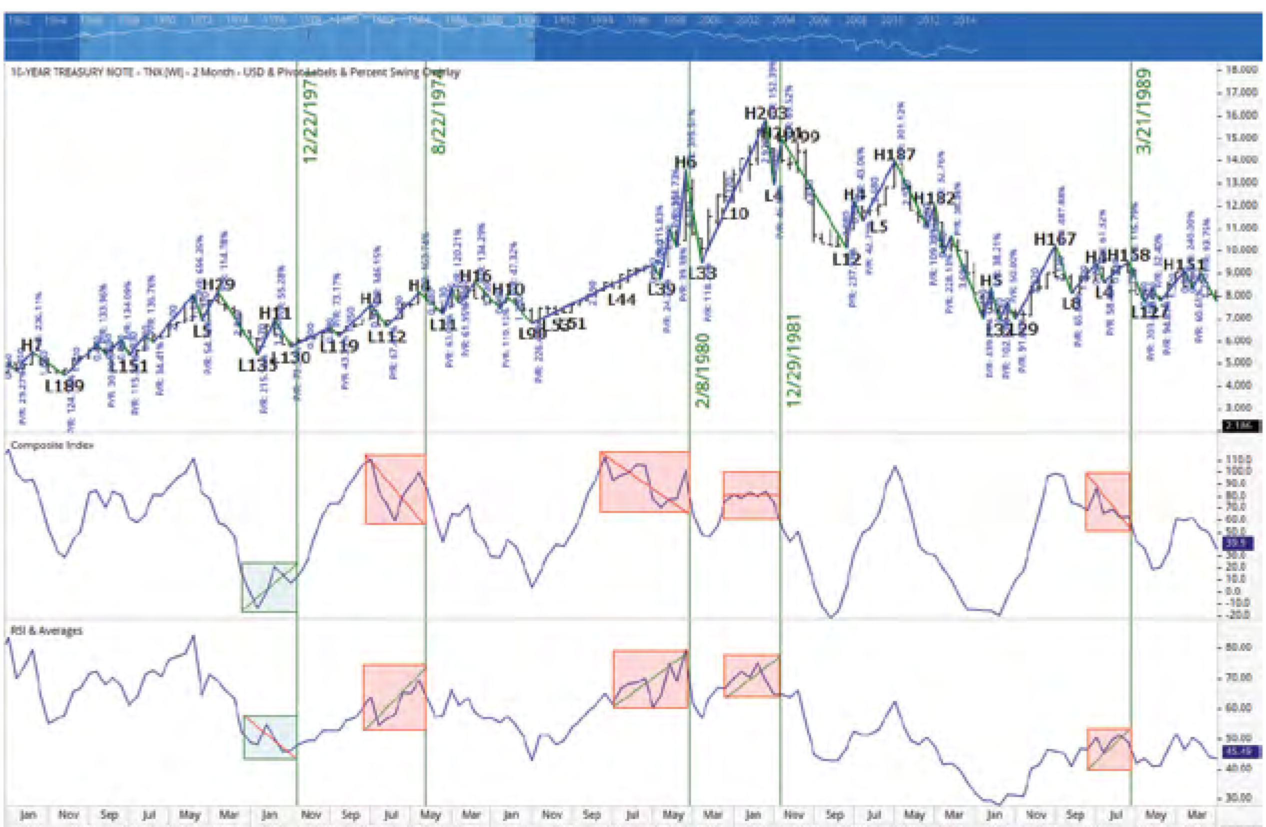


Table 5. 10-Year U.S. Treasury Note Yields—Two-Month Bar Chart Divergence Signal Analysis

	A	B	C	D	E	F	G	H	I
93									
94	**10-Year U.S. Treasury Note Yields - 2 month Bar Chart**								
95				Linear Regression	Swing	# Bars		Percent Retrace	
96	Signal Date	Range	Reversal Swing*	Divergence	Price	Swing H/L	Move	Following Signal	Divergence Signal
97		Prior Swing	Criteria Test	Signal	High/Low	Exceeded	After Signal	to prior Swing	Pass/Fail
98			(see below)	(6 Bar LR)		(>=H/L3?)		(> 35.0 %?)	
99									
100	12/9/2008	-2.286	passed	Buy	L- 2.038	L16	1.976	86.44	passed
101	11/12/2001	-1.411	passed	Buy	L- 4.096	L4	1.361	96.46	passed
102	3/21/1989	0.880	passed	Sell	H- 9.41	H158 (active)	-1.790	203.41	passed
103	12/29/1981	2.030	passed	Sell	H- 14.95	L199 (active)	-4.830	237.93	passed
104	2/8/1980	3.520	passed	Sell	H- 13.17	H6	-4.180	118.75	passed
105	8/22/1974	1.490	passed	Sell	H- 6.16	H4	-0.940	63.09	passed
106	12/22/1971	-1.230	passed	Buy	L- 5.85	L130	0.500	73.17	passed
107									
108									
109	* Swing Criteria Test: Bar= 1, Percent= 5.0, Calculate Using: High/Low								
110	example:	If start of swing is a high; 5% is calculated by							
111		High - (High x 0.5), if prior swing length = 100 at least $5 retracement.							
112		Bar = 1 means criteria is true with each new bar. However, the 5% reversal must be 'true' to create/terminate a new swing.							
113									
114									
115	**10-Year Japanese Govt Bond (Floor Only) -TSE - 1 month Bar Chart**								
116				Linear Regression	Swing	# Bars		Percent Retrace	
117	Signal Date	Price Range	Reversal Swing*	Divergence	Price	Swing H/L	Price Move	Following Signal	Divergence Signal
118		Prior Swing	Criteria Test	Signal	High/Low	Exceeded	After Signal	to prior Swing	Pass/Fail
119			(see below)	(6 Bar LR)		(>H/L3?)		(> 35.0 %?)	
120									
121	3/21/2013	8.7	passed	Sell	H-146	H18	-4.0	61.72	passed
122	7/8/2005	8.2	passed	Sell	H-141	H33	-11.0	135.21	passed
123	7/5/2004	-7.0	passed	Buy	L- 133	L19	8.2	116.76	passed
124	6/12/2003	9.5	passed	Sell	H- 145	H114	-10.9	114.73	passed
125	8/8/1999	-4.3	passed	Buy	L- 128	L192 (active)	13.8	320.93	passed
126	11/11/1997	-3.0	failed 2**	Sell	H-131	L2	2.0	-	failed 2**
127									
128						2** Signal falls in the middle of a Swing			
129	* Swing Criteria Test: Bar= 1, Percent= 3.0, Calculate Using: High/Low								
130	example:	If start of swing is a high; 3% is calculated by							
131		High - (High x 0.3), if prior swing length = 100 at least $3 retracement.							
132		Bar = 1 means criteria is true with each new bar. However, the 3% reversal must be 'true' to create/terminate a new swing.							

NOTE: From 1966 to 2015, there were seven divergence signals in a two-month 10-Year U.S. Treasury Note Yields bar chart. Three signals were 'Sell' signals and four were 'Buy' signals. All seven signals produced percentage retracements greater than 35% relative to the prior swing preceding the divergence signal. Figure 9. 10-Year Japanese Government Bond (Floor Only) TSE—Monthly Bar Chart and Percent Swing Overlay. (1992—2015) (divergences visually determined)

Figure 9. 10-Year Japanese Government Bond (Floor Only) TSE—Monthly Bar Chart and Percent Swing Overlay (1992–2015) (divergences visually determined)

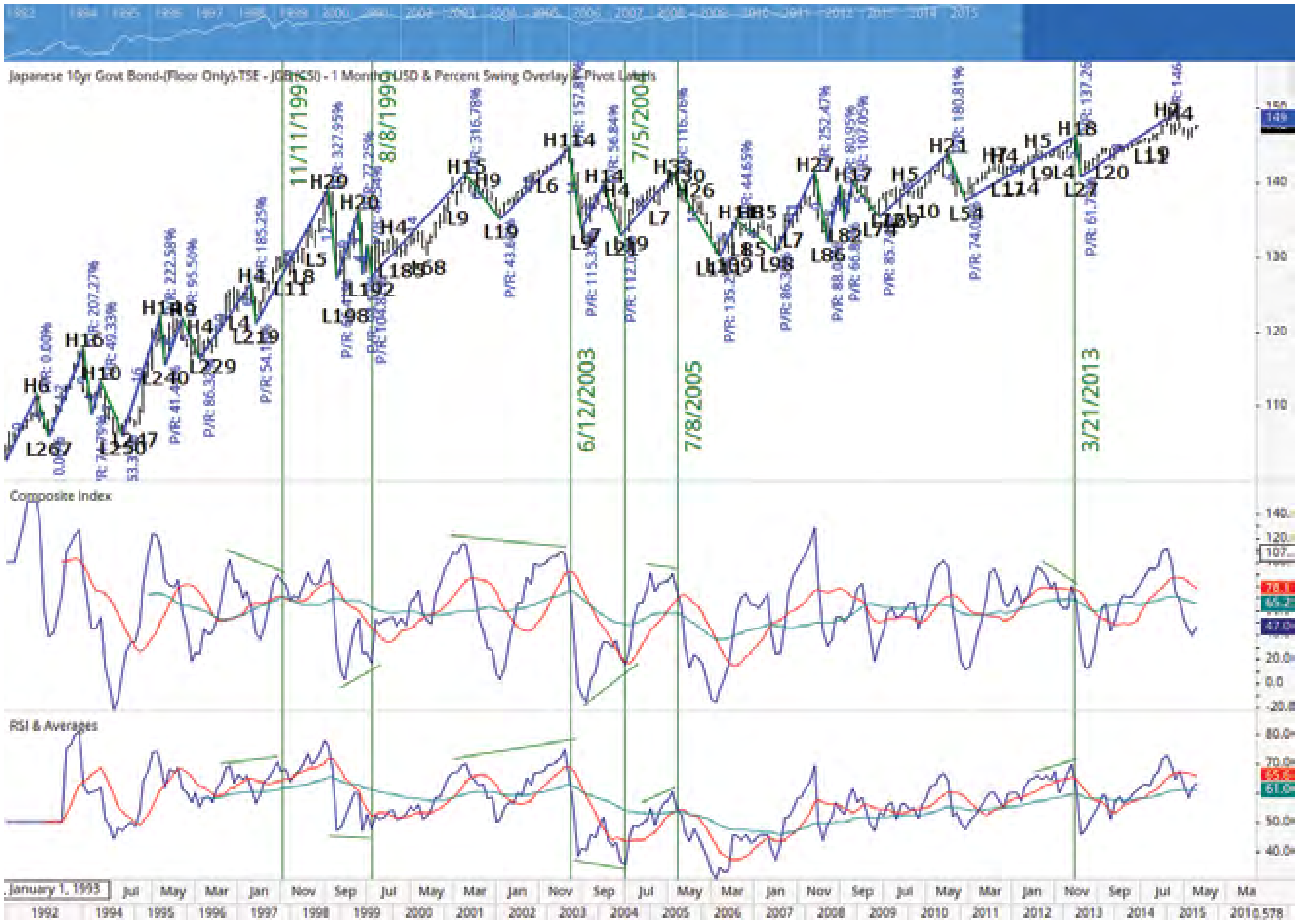


Table 6. 10-Year Japanese Government Bond (Floor Only) TSE—Monthly Bar Chart Divergence Signal Analysis

10-Year Japanese Govt Bond (Floor Only) -TSE - 1 month Bar Chart

Signal Date	Price Range Prior Swing	Reversal Swing* Criteria Test (see below)	Linear Regression Divergence Signal (6 Bar LR)	Swing Price High/Low	# Bars Swing H/L Exceeded (>H/L3?)	Price Move After Signal	Percent Retrace Following Signal to prior Swing (> 35.0 %?)	Divergence Signal Pass/Fail
3/21/2013	8.7	passed	Sell	H-146	H18	-4.0	61.72	passed
7/8/2005	8.2	passed	Sell	H-141	H33	-11.0	135.21	passed
7/5/2004	-7.0	passed	Buy	L- 133	L19	8.2	116.76	passed
6/12/2003	9.5	passed	Sell	H- 145	H114	-10.9	114.73	passed
8/8/1999	-4.3	passed	Buy	L- 128	L192 (active)	13.8	320.93	passed
11/11/1997	-3.0	failed 2**	Sell	H-131	L2	2.0	-	failed 2**

2** Signal falls in the middle of a Swing

* Swing Criteria Test: Bar= 1, Percent= 3.0, Calculate Using: High/Low
example: If start of swing is a high; 3% is calculated by
High - (High x 0.3), if prior swing length = 100 at least $3 retracement.
Bar = 1 means criteria is true with each new bar. However, the 3% reversal must be 'true' to create/terminate a new swing.

During the writing of this paper, numerous observations were made during the Beta testing period of the software that led to changes. When the monthly Japanese Government Bond (JGB) market was tested, the Divergence tool was not the same as the markets tested in Figures 1 through 8. Therefore these results are added for information purposes only and will not be considered in the discussion or conclusion sections. The divergence signals were determined visually by comparing where the Composite Index diverged from the RSI. However the signal still had to be near a swing pivot and exceed a 35% retracement of the prior swing.

From 1992 to 2015, there were six divergence signals. Four were 'Sell' signals and two were 'Buy' signals in the JGB monthly bar chart. Only one divergence signal failed as it developed within a trending price swing, and the price was exceeded two bars later.

Discussion

While the results are very favorable for the Composite Index compared to the RSI, this study is going to immediately raise a question for the reader who is in a trading environment. 'Does the Composite Index provide divergence signals when the RSI does not in other markets and in other timeframes? The author is a global equity index specialist. It has only been used in financial markets and specifically with financial futures contracts for trading. Experience has shown that the Composite Index can be used within long horizon and short horizon timeframes. However, charts displaying long horizon Government Treasury market data will find that the Composite Index will have more frequent and timely divergences if the oscillator is applied to yields. However, traders will find it of value in treasury futures markets in shorter horizon charts of weekly and shorter intervals because the trends are more distinctive in these shorter time periods.

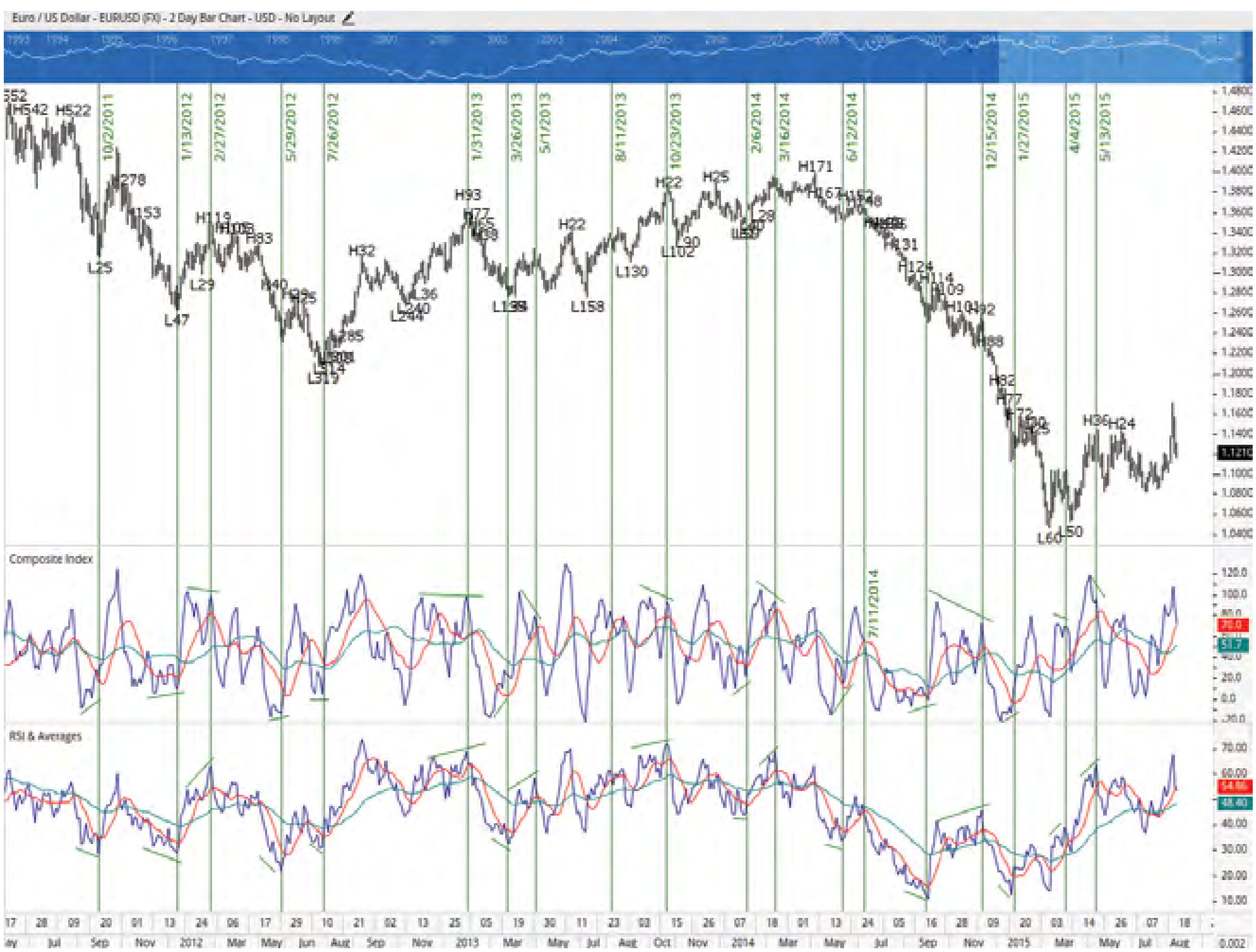
Intraday signals of divergence have been observed for nearly 30 years on S&P500 futures. In this market, the Composite Index has had extensive real-time use.

Consider Figure 10 showing the EURUSD in a two-day bar chart. The divergence signals between the Composite Index and RSI have been marked in Figure 10. The favored time period is a two- or three-day bar chart because this interval is favored by Gann analysts. The two- or three-day bar chart will help develop Elliott wave interpretations. But always pair the signal with a longer period chart, such as a two-day against a weekly chart, or a weekly against a monthly chart. The time ratio of 1:4 is used for intraday comparisons (e.g., a 240-minute chart against a 60-minute chart). When both charts show divergence signals, there is a very high probability of a near trend reversal.

The Composite Index can be used alone under price data, as that is the same divergence pattern. It does not have to be a comparison between the RSI and Composite Index to generate the divergence signal.

Because the Composite Index can oscillate freely to an unrestricted amplitude high or low, it is important to draw horizontal lines on the oscillator when these extremes have occurred. Historic extremes in the DJIA, such as the start of World Wars I and II and 2008, move the Composite Index to new extreme lows, but then the DJIA used these prior panic extremes as meaningful support levels before launching new rallies.

Figure 10. EURUSD—Two-Day Bar Chart with Pivot Labels and Divergence Signals Between Composite Index and RSI (including simple moving average on the oscillators)



The Composite Index can be used for developing Elliott Wave Principle[5] patterns. The Composite Index will form the maximum displacement at a third-of-third Elliott wave. The divergence comes with the fifth of a third wave. A second divergence with the third oscillator peaks at the final fifth wave. This has been a major help for the author for many years.

Many investors and traders couple RSI with MACD. The purpose and expectation for this is to use the faster oscillating RSI against the longer MACD to improve timing. However, the failure of RSI to develop divergence signals at critical junctions is a problem for them.

Consider the German DAX two-month bar chart in Figure 11. The Composite Index has replaced the RSI that is normally plotted over the MACD. In Figure 11, a 5/25/5 period MACD is being used.

The Composite Index may offer a stronger pairing with MACD due to the ability of the oscillator to form divergence signals where the RSI consistently showed a problem exists.

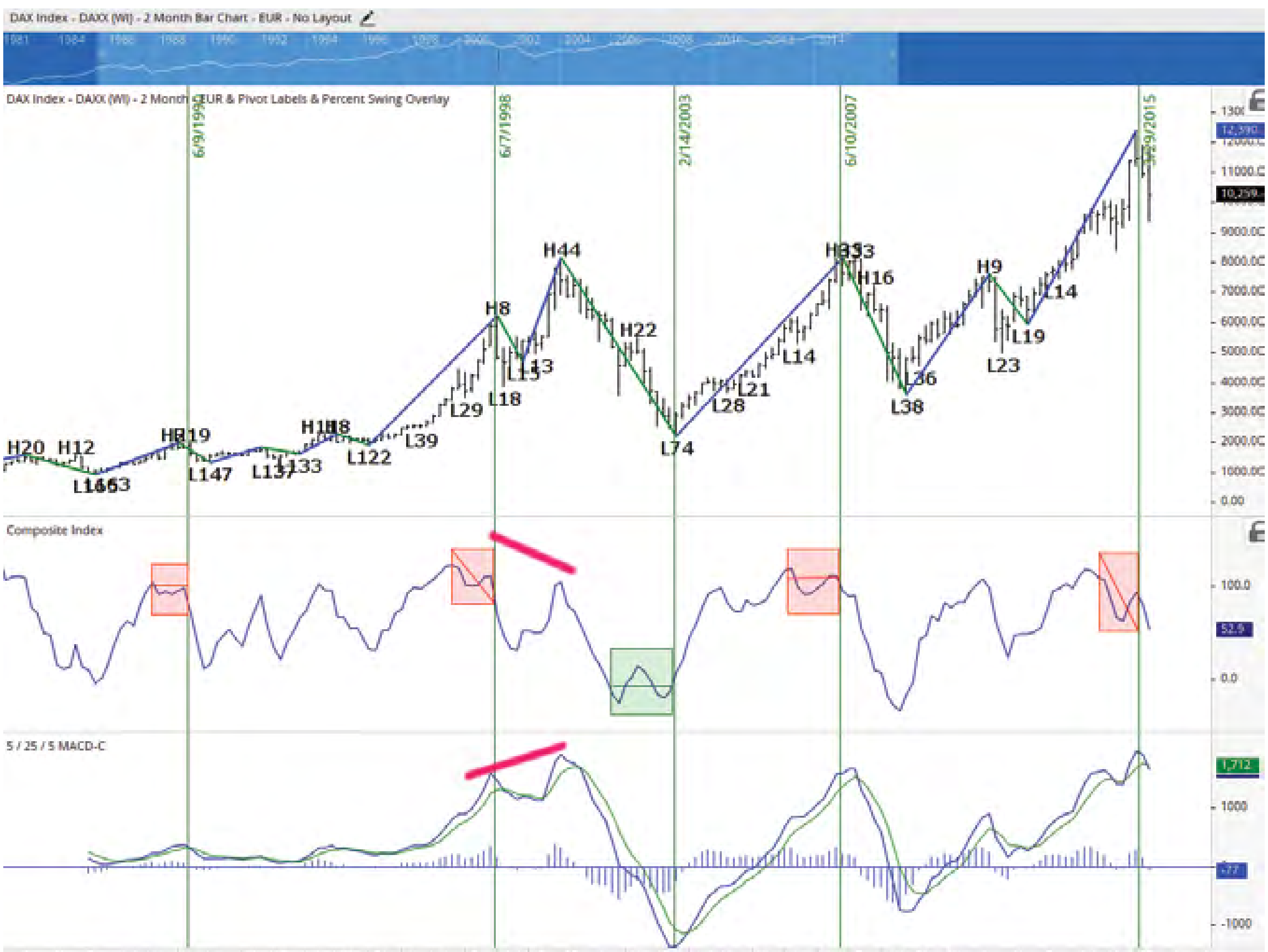
Figure 12 shows a long-horizon two-month bar chart again for the German DAX and DJIA. One of the lessons learned from this study was that divergence does not always have to be a comparison between diverging oscillator peaks. Consider the sharp price drop in the DJIA in 2008. Market-Analyst in this final version of the Divergence tool is able to define divergences when a sharp 'V' pattern develops. In hindsight, the author has always recognized this to be a form of divergence but never had the tools to present the pattern in a provable way. Sharp 'V' bottoms or tops in the Composite Index versus the conventional W's and M's in the RSI should be read as divergence between these oscillators because the RSI is lagging.

Conclusion

The conclusion that should first be made is that the Relative Strength Index displayed a serious problem across six markets in long-horizon charts by failing to develop a divergence signal 42 times (excluding the six additional JGB signals). In most cases the failure to provide a warning signal in this study was followed by a major price trend reversal that would have been extremely costly for asset managers.

The Composite Index triggered 17 'Buy' signals and 25 'Sell' signals for a total of 42 divergences against the RSI. It can be

Figure 11. German DAX Two-Month Bar Chart with Composite Index and 5/25/5 MACD



suggested that anyone currently using RSI would benefit from adding the Composite Index to their screen. Four signals remained open today because the market has neither triggered a pass nor fail result. Thirty-three signals passed, while only five failed. The Composite Index showed an exceptional performance in the long-term horizon of monthly or two-month bar charts.

Notes

[1] Wilder, Welles J., *New Concepts in Technical Trading Systems, 1978*

[2] Appel, Gerald., *Technical Analysis: Power Tools for Active Investors, 2005, page 165*

[3] Brown, Constance M., *Technical Analysis for the Trading Professional, Second Edition McGraw-Hill, 2012, page 369*

[4] The Market Technician Association's *Journal of Technical Analysis (Winter 1993-Spring 1994; 42: page 45) The Derivative Oscillator: A New Approach for an Old Problem by Connie Brown. A copy of this paper can be downloaded from* www.aeroinvest.com/books.htm

[5] Frost, A.J., and Prechter, Robert R., *Elliott Wave Principle: Key to Market Behavior, 2005*

[6] Market-Analyst Software, Version 8 is available from http://www.mav7.com/

Additional Notes

The last four 'open' sell signals in the German DAX, French CAC, China Shanghai Composite, and Dow Jones Industrial Average should now read "passed" due to the January 2016 declines. Therefore thirty-seven signals passed, while only five failed.

This paper has been edited for publication. To obtain the full version, please email support@aeroinvest.com.

The Composite Index is now a standard tool in Market-Analyst. Bloomberg will add it by request. It is also now in the public domain for eSignal and CQG.

FIGURE 12. 2-month German Dax (left) and 2-month DJIA (right) displaying the final Divergence tool in Market-Analyst.

Trend Without Hiccups—A Kalman Filter Approach

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Abstract

Have you ever felt miserable because of a sudden whipsaw in the price that triggered an unfortunate trade? In an attempt to remove this noise, technical analysts have used various types of moving averages (simple, exponential, adaptive one or using Nyquist criterion). These tools may have performed decently, but we show in this paper that this can be improved dramatically thanks to the optimal filtering theory of Kalman filters (KF). We explain the basic concepts of KF and its optimum criterion. We provide a pseudo code for this new technical indicator that demystifies its complexity. We show that this new smoothing device can be used to better forecast price moves as lag is reduced. We provide four Kalman filter models and their performance on the SP500 mini- future contract. Results are quite illustrative of the efficiency of KF models, with better net performance achieved by the KF model combining smoothing and extremum position.

The author would like to acknowledge support from Thomson Reuters. Data are from Thomson Reuters Eikon, while screenshots and source codes are done with TR Eikon Trading Robot. The author also thanks Denis Dollfus for fruitful conversations.

The author also warns that the views and opinions expressed in this article are those of the author and do not necessarily reflect the official position or policy of Thomson Reuters.

Introduction

Have you ever felt angry because a sudden price whipsaw triggered an unfortunate signal and a resulting bad trade? Prices have inherent blips and jerks that are not easy to control. Moreover, prices are inputs for technical analysis indicators. This can result in corrupted or non-efficient indicators. In an ideal world, one would like prices heading to a clear direction. Remember the old adage: " trade with the trend" . But in real life, price hiccups create noise and perturb the signal.

A first attempt to remove these yanks and jolts is to smoothen prices with moving averages. However, moving averages suffer from two flaws: lags and no dynamics. The first drawback—delay in moving average response—is widely known as moving averages used past data. Adaptations to moving averages have been suggested (exponential, adaptive, zero lag or Nyquist criterion based moving averages). Dürschner (2012) suggested the use of Nyquist criterion to create moving average 3.0 with no lag.

This is intellectually very enticing, as the lag is completely removed. This improves moving averages from Patrick Mulloy (Mulloy, 1994) with zero lag or the attempts by John Ehlers to provide sophisticated moving averages (Ehlers, 2001a or Ehlers, 2001b). But this does not address the second problem of capturing price dynamics. What we mean by price dynamics is the price movement. If we can identify that prices are moving upwards (respectively downwards), then a good guess for the next price observation should be higher (respectively lower) than the current price.

Let us pause for a moment and imagine that instead of prices, we were looking at car position using a GPS. We measure the car position with a GPS but with some noise, as the signal is not perfectlyaccurate. Could we capture the car dynamics to compute the best guess at next time step 1 and hence, reduce noise in car position? The answer is yes! And guess what, this is what your car GPS is doing. This theory simply explained is referred to as Kalman filter, from its inventor, Kalman (1960), shortened to KF in this paper. It was created for the spatial industry to remove noise and capture shuttle movements. In a scientific way, the Kalman filter is an efficient recursive filter that estimates the state of a dynamic system from a series of incomplete and noisy measurements to estimate the best forecast according to an assumed distribution.

In the original paper, Kalman assumes a Gaussian distribution of noise, but an extended version can now cope with more advanced distribution (see Wikipedia, Kalman Filter). In this article, we first revisit moving averages and then present different Kalman filter models and their implementation to create trading strategies. We then provide performance results for our four KF models on one year of data of the E-mini-SP continuation future.

Motivation for Smoothing

Smoothing prices is natural. The basic idea is to remove noise from prices to better identify important patterns or trends. Remember, when we trade, we want the big picture. So smoothing enables us to remove bumps, bangs, bounces, and shocks and get an average clean signal. If we believe that prices do not follow a random walk model, the smoothened signal provides us a clear directional signal.

Impact for Trading Strategies

Conversely, if we do not smoothen prices, we could act on tugs, wrenches, or snatches that are against the trend and result in bad trades. Smoothing is the right way! But we need to be careful. If we smoothen with lag (one of the major drawbacks of moving averages), we act with delay and enter trades too late, potentially facing reverse direction markets. In an ideal world, we would like the smoothing technique to have zero lag and to provide a first move advantage.

Material and Methods

Review of Moving Average

The usual moving averages

The usual way to remove noise in prices is with moving averages. Let us denote weights by w_i for the time T_i , where goes between 0 and N Then, the moving average is given by

$$MA(w_0, \dots, w_N) = \sum_{i=0}^{N} w_i P_i \quad \text{(EQ 2.1)}$$

Whose lag is

$$LAG\ MA(w_0, \dots, w_N) = \frac{\sum_{i=0}^{N} w_i T_i}{\sum_{i=0}^{N} w_i} \quad \text{(EQ 2.2)}$$

If we do a moving average of a moving avera°ge, the equation (2.1) becomes

$$MA \odot MA(w_0, \dots, w_N) = \sum_{i=0}^{N} w_i \left(\sum_{j=0}^{N} w_j P_{i+j}\right) \quad \text{(EQ 2.3)}$$

And the corresponding lag is

$$LAG\ MA \odot MA(w_0, \dots, w_N) = \frac{\sum_{i=0,j=0}^{N} w_i w_j T_{i+j}}{\sum_{i=0,j=0}^{N} w_i w_j} \quad \text{(EQ 2.4)}$$

We can easily derive a similar formula for a recursive moving average at the order kth:

$$MA \odot^k (w_0, \dots, w_N) = \sum_{i_1=0,\dots,i_k=0}^{N} w_{i_1} \dots w_{i_k} P_{i_1+\dots+i_k} \quad \text{(EQ 2.5)}$$

The resulting lag is

$$LAG\ MA \odot^k (w_0, \dots, w_N) = \frac{\sum_{i_1=0,\dots,i_k=0}^{N} w_{i_1} \dots w_{i_k} T_{i_1+\dots+i_k}}{\sum_{i_1=0,\dots,i_k=0}^{N} w_{i_1} \dots w_{i_k}} \quad \text{(EQ 2.6)}$$

Explicit Lag Computation

Prices are sampled with equidistant time steps Formulae $T_i = \frac{i}{N} T$ (EQ.2.6) can be easily computed in terms of first order value, as follows: (See Proof A.1:)

$$LAG\ MA \odot^k (w_0, \dots, w_N) = k\ \ LAG\ MA(w_0, \dots, w_N) \quad \text{(EQ 2.7)}$$

Furthermore, if we combine recursive moving averages, it is easy to find back the results of Mulloy. In the case of a moving average of moving average, the only possible choice with zero lag whose coefficient sum is equal to 1 is the double moving average: (See Proof A.2)

$$DEMA = 2MA\text{-}\ MA \odot^2 \quad \text{(EQ 2.8)}$$

And for the triple moving average (if we impose the additional constraint that the third order recursive moving average coefficient is 1), we have (See Proof A.3)

$$TEMA = 3MA\text{-}\ 3.MA \odot^2 + MA \odot^3 \quad \text{(EQ 2.9)}$$

Introduction to Kalman Filter

Basic concepts

Kalman filter is a recursive algorithm that was invented in the 1960s to track a moving target, remove any noisy measurements of its position, and predict its future position. In finance, KF has been used by the asset management industry for various purposes. KF is an optimal choice in many cases and does at least better than a moving average smoothing. Dao et al. (Bruder, Dao, Richard, and Roncalli, 2011) and (Dao, 2011) showed that for price following random walk with noise, KF is equivalent to the optimal exponential moving average with parameter equal to Kalman gain. However, for more sophisticated dynamics, like a linear Gaussian model, KF is the optimal choice and the most efficient computational solution for finding the model parameters.

In finance, KF has also been used over the last decade by different authors. Martinelli and Rhoads in (Martinelli, 2006) and (Martinelli and Rhoads, 2010) used Kalman filter to find the optimal guess for trading strategies on stocks. Haleh et al. (2011) used Extended Kalman filter for forecasting stock prices, combining technical and fundamental data. They showed that it outperformed regression and neural networks. Ernie Chan (2013) suggested using KF for pair correlation trading, while Cazalet and Zheng (2014) used KF for hedge fund replication.

In a general way, Kalman filter is considered a linear dynamic system given by

$$X_{t+1} = \phi X_t + c_t + w_t \quad \text{(EQ 3.1)}$$

$$Y_t = H X_t + d_t + v_t \quad \text{(EQ 3.2)}$$

Where Φ is the state transition matrix, H the measurement matrix, w_t the model noise, X_t the state vector, Y_t the measurement vector, v_t the measurement noise, w_t and v_t the independent white noises with zero mean and their variance matrices given by Q and R respectively. c_t, respectively d_t, is the drift of the state vector, respectively the measurement vector. The corresponding Kalman filter is:

Prediction step: $$X_{t+1|t} = \phi X_{t|t} + c_t \quad \text{(EQ.3.3)}$$

With $$P_{t+1|t} = \phi P_{t|t} \phi^T + Q \quad \text{(EQ.3.4)}$$

Correction step: $$X_{t+1} = X_{t+1|t} + K_{t+1}\left(Y_{t+1} - Y_{t+1|t}\right) \quad \text{(EQ.3.5)}$$

With $$Y_{t+1|t} = H X_t + d_t$$

With Kalman gain $$K_{t+1} = P_{t+1|t} H^T \left[H P_{t+1|t} H^T + R\right]^{-1} \quad \text{(EQ.3.6)}$$

With $$P_{t+1|t+1} = [I - K_{t+1} H] P_{t+1|t} \quad \text{(EQ.3.7)}$$

KF works in a two-step process (prediction and correction steps). The algorithm is recursive and can run in real time, using only the present input measurements, the previously calculated state, and its uncertainty matrix.

Obviously, one needs to specify the state and measurement vector. A logical choice is to use a physical system with concepts similar to speed and acceleration:

$$x_{t+1} = x_t + \dot{x}_t \delta t + 1/2\, a_t \delta t^2 \quad \text{(EQ.3.8)}$$

$$\dot{x}_{t+1} = \dot{x}_t + a_t \delta t \quad \text{(EQ.3.9)}$$

$$y_t = x_t + v_t \quad \text{(EQ.3.10)}$$

Where $\dot{x}_t$ and x_t are price and rate of change of stock price at time *t* (similar to position and speed). a_t can be seen as the acceleration of price at time *t* It is considered to be a model noise. *T* is the sampling period, y_t the measurement, v_t the measurement noise.

This can be analyzed as a KF system with

$$X_t = \begin{bmatrix} x_t \\ \dot{x}_t \end{bmatrix}, \phi = \begin{bmatrix} 1 & \delta t \\ 0 & 1 \end{bmatrix}, w_t = \begin{bmatrix} \frac{1}{2}\delta t^2 \\ \delta t \end{bmatrix} a_t, H = [1 \quad 0], c_t = 0 \quad \text{(EQ.3.11)}$$

This is named model 1. This model has the advantage to take into account a certain dynamic compared to the simple Random Walk model that is often used in the KF literature, where there is no speed term. In our model 1, The speed is initially estimated as the difference between two consecutive prices. The parameters to estimate are the following (four in total)

$$Q = \begin{bmatrix} p_1 p_1 & p_2 p_1 \\ p_1 p_2 & p_2 p_2 \end{bmatrix}, R = [p_3], P_{t=0} = \begin{bmatrix} p_4 & 0 \\ 0 & p_4 \end{bmatrix} \quad \text{(EQ.3.12)}$$

It is interesting to note that this model is very close to a local linear trend model. Indeed, the local linear trend model writes as

$$x_{t+1} = x_t + \beta_t + w_{1,t} \quad \text{(EQ.3.13)}$$

$$\beta_{t+1} = \beta_t + w_{2,t} \quad \text{(EQ.3.14)}$$

$$y_t = x_t + v_t \quad \text{(EQ.3.15)}$$

We can notice that in this specific case, the KF parameters are the following:

$$X_t = \begin{bmatrix} x_t \\ \beta_t \end{bmatrix}, \phi = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, w_t = \begin{bmatrix} w_{1,t} \\ w_{2,t} \end{bmatrix}, H = [1 \quad 0], c_t = 0 \quad \text{(EQ.3.16)}$$

The parameters to estimate are the following (five in total)

$$Q = \begin{bmatrix} p_1 p_1 & p_2 p_1 \\ p_1 p_2 & p_2 p_2 \end{bmatrix}, R = [p_3], P_{t=0} = \begin{bmatrix} p_4 & 0 \\ 0 & p_5 \end{bmatrix} \quad \text{(EQ.3.17)}$$

This model has almost the same parameters as model 1. This is named model 2. Comparing equation 3.12 and 3.17, we know that models 1 and 2 should have very similar behavior.

We can create a more general two-factor model with contribution to price split between a short term x_t^1 and a long term x_t^2. This leads to:

In this specific model, we have the following parameters

$$x_{t+1}^1 = a_{11} x_t^1 + a_{12} x_t^2 + w_{1,t} \quad \text{(EQ.3.18)}$$

$$x_{t+1}^2 = a_{22} x_t^2 + w_{2,t} \quad \text{(EQ.3.19)}$$

$$y_t = h_1 x_t^1 + h_2 x_t^2 + v_t \quad \text{(EQ.3.20)}$$

$$X_t = \begin{bmatrix} x_t^1 \\ x_t^2 \end{bmatrix}, \phi = \begin{bmatrix} a_{11} & a_{12} \\ 0 & a_{22} \end{bmatrix}, w_t = \begin{bmatrix} w_{1,t} \\ w_{2,t} \end{bmatrix}, H = \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}, c_t = 0 \quad \text{(EQ.3.21)}$$

We call this model 3. Because of its generality, this model encompasses models 1 and 2. The parameters to estimate are the following (10 in total)

$$\phi = \begin{bmatrix} p_1 & p_2 \\ 0 & p_3 \end{bmatrix}, H = \begin{bmatrix} p_4 \\ p_5 \end{bmatrix}, Q = \begin{bmatrix} p_6 p_6 & p_7 p_6 \\ p_6 p_7 & p_7 p_7 \end{bmatrix}, R = [p_8], P_{t=0} = \begin{bmatrix} p_9 & 0 \\ 0 & p_{10} \end{bmatrix} \quad \text{(EQ.3.22)}$$

The last model we use is a model inspired by a combination of oscillators and the previous model. In this model, we use the price position with respect to its extremum as in the fast stochastic oscillator. We denote the variable over a d period given by

$$K_t^d = \frac{\text{Current Close} - \text{Lowest Low(d)}}{\text{Highest High(d)} - \text{Lowest Low(d)}} \times 100 \quad \text{(EQ.3.23)}$$

We denote by L_t^d = *Lowest Low (d)* and H_t^d = *Highest High (d)* the lowest low and highest high over d period. We use in our example a 14-day period. As in model 3, we also split the contribution of the price due to short term x_t^1 and long term x_t^2. This leads to:

$$x_{t+1}^1 = a_{11} x_t^1 + a_{12} x_t^2 + \left(M_1 - N_1 K_t^d\right) + w_{1,t} \quad \text{(EQ.3.24)}$$

$$x_{t+1}^2 = a_{22} x_t^2 + \left(M_2 - N_2 K_t^d\right) + w_{2,t} \quad \text{(EQ.3.25)}$$

With

$$K_t^d = \frac{h_0 x_t - L_t^d}{H_t^d - L_t^d} \quad \text{(EQ.3.26)}$$

$$y_t = h_1 x_t^1 + h_2 x_t^2 + v_t \quad \text{(EQ.3.27)}$$

In this specific model, we have the following parameters

$$X_t = \begin{bmatrix} x_t^1 \\ x_t^2 \end{bmatrix}, \phi = \begin{bmatrix} a_{11} & a_{12} \\ 0 & a_{22} \end{bmatrix}, w_t = \begin{bmatrix} w_{1,t} \\ w_{2,t} \end{bmatrix}, H = \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}, c_t = \begin{pmatrix} M_1 - N_1 K_t^d \\ M_2 - N_2 K_t^d \end{pmatrix} \quad \text{(EQ.3.28)}$$

We call this model 4. Because of its generality, this model encompasses models 1, 2 and 3. It captures short and long-term effect as well as position with regard to extrema like what oscillators do. This is by far the most realistic model. Short-term factor x_t^1 models extreme market reactions that last for a few days. Long-term factor x_t^2 is only influenced by itself and not by the short term x_t^1 The parameters to estimate are the following (15 in total) (the same set as model 3 and five additional parameters)

$$\phi = \begin{bmatrix} p_1 & p_2 \\ 0 & p_3 \end{bmatrix}, H = \begin{bmatrix} p_4 \\ p_5 \end{bmatrix}, Q = \begin{bmatrix} p_6 p_6 & p_7 p_6 \\ p_6 p_7 & p_7 p_7 \end{bmatrix}. R = [p_8], P_{t=0} = \begin{bmatrix} p_9 & 0 \\ 0 & p_{10} \end{bmatrix} \quad \text{(EQ.3.29}$$

$$c_t = \begin{pmatrix} p_{11} - p_{12} K_t^d \\ p_{13} - p_{14} K_t^d \end{pmatrix}, p_{14} = d \quad \text{(EQ.3.30)}$$

Pseudo code

```
/// Initialization phases: parameters contains
///         - initial value for model state + measurement of model
///         - measurement of state and model variance
Kalman2D k = new Kalman2D(parameters);
k.Setup( parameters );
int length = timeSeries.Length;

Point2D[] kalmanResult = new Point2D[length];
/// the loop to update in real time
for( int i = 0; i<length; ++i )
{
        if( i<Period )
        {
                k.Predict();
                k.Update(timeSeries[i]);

                kalmanResult.Set(0, timeSeries[i]);
                kalmanResult.Set(1, timeSeries[i]);
        }
        else
        {
                k.Predict();
                kalmanResult.Set(0, k.X.Get(0,0) );
                k.Update(timeSeries[i]);
                kalmanResult.Set(1, k.X.Get(0,0) );
        }
}
```

Trading Strategies With Kalman Filter

Basic concepts

The KF model enables various things:

- It smoothens any data. Hence, the data produced by the KF can be used instead of prices to remove any spike. This opens multiple options, as these inputs can be used in crossover moving averages strategies, MACD indicator, oscillators, and a combination of these. We do not explore this, as the paper goal is to study the predictive power of KF models.
- It can be used as a predictive tool to help in deciding when to enter long or short strategies. We compare the prediction with the current. This is precisely the subject of this paper.

Pseudo code

```
/// <summary>
/// Called on each new bar event
/// </summary>
protected override void OnNewBar()
{
if (KalmanFilter(Param1,..,ParamN).Predict[0] > Close[1]+Offset)
        EnterLong();
else if (KalmanFilter(Param1,..,ParamN).Predict[0] < Close [1]-Offset)
        EnterShort();}
}
```

Results

Numerical Results

Description of the sample set

To test the efficiency of KF models 1, 2, 3 and 4, we use the E-mini-S& P-500 continuation Future, whose RIC is Esc1. We use the Eikon App "Trading Robot" that has been developed by the author. We look at daily data between 28 Feb 2015 and 28 Feb 2016.

Comparison of Kalman filters with standard technical indicators.

We provide graphics of various indicators to measure how KFs best fit price information. We display

- Some standard technical analysis indicators:
  - » Moving averages with lag: standard and exponential moving average with 12 days period.
  - » Moving averages with zero lag: double exponential moving average with 12 days period as (EQ.2.9) and triple exponential moving average with 12 days period as (EQ.2.10).
- The different KF indicators, KF model 1, 2, 3 and 4.

In Figure 1, we see that the KF model 1 sticks much better to price data than any of the two moving averages. This is normal, as KF model has 0 to 1 period lag. We do not show in this graphic the other KF models, as they would be barely distinguishable. In Figure 2 and Figure 3, we compare KF model with zero-lag moving averages like DEMA or TEMA. We emphasize the area of difference with orange circles and see that KF models stick much better to price data. In Figure 4, we compare the different KF models and see that KF models 1 and 2 are similar while models 3 and 4 are also similar, with an advantage to the latter ones.

Kalman filter trading strategies performance

We look at the same one year of data and compute the optimal parameters for the four KF models. For each model, we use no leverage and trade only one future contract regardless of the current trading account. We also assume a $4 USD roundtrip commission, which is the observed price at retailed brokers like Interactive-Brokers. For a large trader with more than 20,000 contracts per month and CME membership, roundtrip commission lowers to $1.4 USD.

Table 1 shows that the best model is model 4, with an annual net profit of $39.5K USD, followed by model 3 with $29K USD, and the last two being models 2 and 1, with net profit of $22K and $19K USD.

We can make various remarks:

- The final model ranking makes sense, as model 4 is richer than 3, which itself is richer than 2 that is richer than 1.
- The best model, KF 4, provides a nice net profit, $39K, with a maximum drawdown of -2,600, hence representing a ratio of net profit over drawdown (also called recovery ratio) of 15. This is excellent!
- E-mini-S&P daily margin is about $5 to $6K USD; hence, $40K USD net profit is an amazing statistic. In addition, model 4 incurs only positive monthly PnL (Figure 5).
- KF model 3 has a nice and steady cumulative profit curve (Figure 6), while model 4 outperforms because it captures a few large additional trades (Figure 5 and Figure 9).
- KF models 1 and 2 are Kalman filter models already explored in literature. We find some negative monthly PnL and large drawdown (see Figure 7 and Figure 8). This is a known feature, as these models have a poor dynamic. This may explain why these standard KF models have been disregarded.

Figure 1: Comparison of Kalman filter with classical moving averages. The red line representing the KF model 1 sticks much better to the price data than any of the two moving averages (standard and exponential ones with both 12 periods).

Figure 2: Comparison of Kalman filter with double and triple exponential moving averages. The red lines representing the KF model 1 stick much better to theprice data than DEMA or TEMA, as displayed in orange circles.

Figure 3: Zoom on differences between Kalman filter and zero lag moving averages. KF model 1 reacts faster to price changes, as emphasized by orange circles.

Figure 4: Comparison between the different Kalman filters. Within the KF model family, models 3 and 4 are even better than models 1 and 2. Models 1 and 2 (respectively models 3 and 4) have similar behaviors.

- The difference between KF model 3 and model 4 is the oscillator factor. This confirms the well-known fact that oscillators capture other features besides trending indicators and catch any mean reverting market (in trading range environment). The combination of trend-following factors (like in model 3) with the new extra term inspired from oscillators yields a powerful model called 4. We can notice that parameter 14, N_2, is null. It indicates that the oscillator factor plays a role only on short-term factors. This can be interpreted as empirical evidence that range trading has only influence on the short term while trend dominates in the long term.
- The parameters 11 and 13 in KF model 4 represent the neutrality level at which the oscillator factors change from bullish to bearish. It is amazing that its optimal value turns out to be 50%, which is also a well-known feature of oscillators where the level of neutrality is 50%

We provide optimal parameters in Table 2. We also provide various statistics for KF models 4, 3, 2 and 1 (starting with the best model and going to the worst) in Table 3, Table 4, Table 5, Table 6, and the list of all trades in Table 7

We provide in Figure 5, Figure 6, Figure 7, and Figure 8 the cumulative profit and loss curve for trading strategy of models 4, 3, 2 and 1, starting with the best one. Figure 9 zooms on the period where model 4 locks in a large profit due to accurate prediction of turning points.

Table 1: Trading performance of Kalman filter models 1, 2, 3 and 4.

Model	Net Profit	Gross Profit	Gross Loss	Drawdown	Trades	Commission	Recovery ratio	Sharpe	Rat io
Kalman Filter 1	18,755	39,151	-20,396	-7,348	55	220	2.55		0.72
Kalman Filter 2	22,380	40,747	-18,367	-7,348	55	220	3.05		0.76
Kalman Filter 3	29,022	47,548	-18,526	-3,800	57	228	7.64		1.22
Kalman Filter 4	39,558	50,243	-10,685	-2,600	48	192	15.21		0.73

Table 2: Model parameters for Kalman filter models 1, 2, 3 and 4.

Model	Kalman Filter 1	Kalman Filter 2	Kalman Filter 3	Kalman Filter 4
Parameter 1	5.00	5.00	1.00	1.00
Parameter 2	5.00	5.00	0.40	0.40
Parameter 3	45.00	41.00	1.20	1.20
Parameter 4	10.00	1.00	1.00	1.00
Parameter 5		1.00	1.00	1.00
Parameter 6			0.80	0.80
Parameter 7			0.40	0.40
Parameter 8			0.70	0.70
Parameter 9			1.00	1.00
Parameter 10			0.40	0.40
Parameter 11				0.50
Parameter 12				0.90
Parameter 13				0.50
Parameter 14				-
Parameter 15				5.00

Table 3: Trading strategy statistics for Kalman filter model 4.

Kalman Filer Model 4			
Field	All	Long	Short
Net Profit (A+B)	39,558	17,279	22,279
Gross Profit (A)	50,243	20,957	29,286
Gross Loss (B)	(10,685)	(3,678)	(7,007)
Tot al Commission	192	96	96
Drawdown	(2,600)	(2,137)	(2,520)
Sharpe Rat io	0.73	0.84	0.55
Profit Fact or (A/ B)	4.70	5.70	4.18
Number of Trades	48	24	24
Winning Trades	30	17	13
Average Trade Profit	824	720	928
Average Winning Trade	1,675	1,233	2,253
Largest Winning Trade	11,309	5,434	11,309
Max. conseq. Winners	6	5	3
Losing Trades	18	7	11
Average Losing Trade	(594)	(525)	(637)
Largest Losing Trade	(1,729)	(1,729)	(1,267)
Max. conseq. Losers	4	2	3
Rat io avg. Win / avg. Loss	2.82	2.35	3.54
Winning/ Tot al	0.63	0.71	0.54
Avg. Time in Market	6.92 days	3.88 days	9.96 days
Profit per Mont h	3,623	1,583	2,047
Max. Time t o Recover	58 days	56 days	92 days

Figure 5: Cumulative profit and monthly PnL distribution for KF model 4.

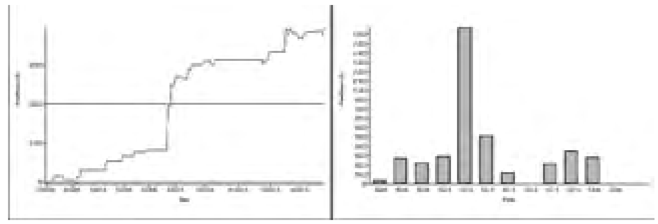

Table 4: Trading strategy statistics for Kalman filter model 3.

Kalman Filer Model 3			
Field	All	Long	Short
Net Profit (A+B)	29,022	12,009	17,013
Gross Profit (A)	47,548	24,403	23,145
Gross Loss (B)	(18,526)	(12,394)	(6,132)
Tot al Commission	228	116	112
Drawdown	(3,820)	(3,366)	(1,579)
Sharpe Rat io	1.22	0.38	1.65
Profit Fact or (A/ B)	2.57	1.97	3.77
Number of Trades	57	29	28
Winning Trades	35	18	17
Average Trade Profit	509	414	608
Average Winning Trade	1,359	1,356	1,361
Largest Winning Trade	5,234	5,234	4,271
Max. conseq. Winners	14	7	7
Losing Trades	22	11	11
Average Losing Trade	(842)	(1,127)	(557)
Largest Losing Trade	(2,879)	(2,879)	(1,579)
Max. conseq. Losers	5	3	3
Ratio avg. Win / avg. Loss	1.61	1.20	2.44
Winning/ Tot al	0.61	0.62	0.61
Avg. Time in Market	5.82 days	6.45 days	5.18 days
Profit per Mont h	2,658	1,100	1,860
Max. Time t o Recover	53 days	64 days	71 days

Figure 6: Cumulative profit and monthly PnL distribution for KF model 3.

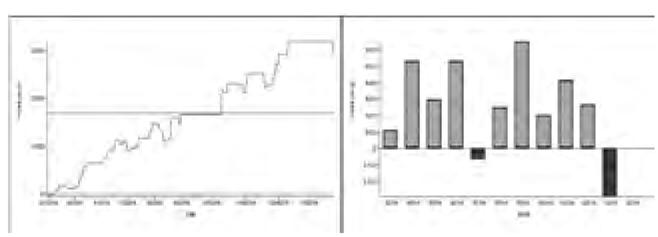

Table 5: Trading strategy statistics for Kalman filter model 2.

Kalman Filer Model 2			
Field	All	Long	Short
Tot al Net Profit	22,380	8,692	13,688
Gross Profit	40,747	19,611	21,136
Gross Loss	(18,367)	(10,919)	(7,448)
Commission	220	108	112
Drawdown	(7,348)	(6,628)	(2,283)
Sharpe Rat io	0.76	0.32	0.55
Profit Fact or	2.22	1.80	2.84
Number of Trades	55	27	28
Winning Trades	32	16	16
Average Trade Profit	407	322	489
Average Winning Trade	1,273	1,226	1,321
Largest Winning Trade	6,521	3,221	6,521
Max. conseq. Winners	4	6	3
Losing Trades	23	11	12
Average Losing Trade	(799)	(993)	(621)
Largest Losing Trade	(3,679)	(3,679)	(1,717)
Max. conseq. Losers	4	5	2
Ratio avg. Win / avg. Loss	1.59	1.23	2.13
Winning/ Tot al	0.58	0.59	0.57
Avg. Time in Market	6.04 days	6.41 days	5.68 days
Profit per Mont h	2,050	801	1,254
Max. Time t o Recover	132 days	146 days	70 days

Table 6: Trading strategy statistics for Kalman filter model 1.

Kalman Filer Model 1			
Field	All	Long	Short
Tot al Net Profit	18,755	6,880	11,876
Gross Profit	39,151	18,861	20,290
Gross Loss	(20,396)	(11,982)	(8,415)
Commission	220	108	112
Drawdown	(7,348)	(6,628)	(2,283)
Sharpe Rat io	0.72	0.26	0.48
Profit Fact or	1.92	1.57	2.41
Number of Trades	55	27	28
Winning Trades	31	16	15
Average Trade Profit	341	255	424
Average Winning Trade	1,263	1,179	1,353
Largest Winning Trade	6,521	3,221	6,521
Max. conseq. Winners	4	6	2
Losing Trades	24	11	13
Average Losing Trade	(850)	(1,089)	(647)
Largest Losing Trade	(3,679)	(3,679)	(1,717)
Max. conseq. Losers	4	5	2
Ratio avg. Win / avg. Loss	1.49	1.08	2.09
Winning/ Tot al	0.56	0.59	0.54
Avg. Time in Market	6.04 days	6.45 days	5.64 days
Profit per Mont h	1,718	634	1,088
Max. Time t o Recover	132 days	146 days	71 days

Figure 7: Cumulative profit and monthly PnL distribution for KF model 2.

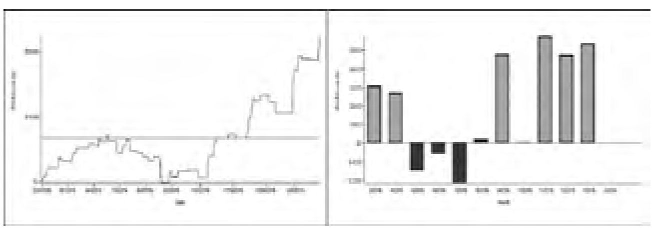

Figure 8: Cumulative profit and monthly PnL distribution for KF model 1.

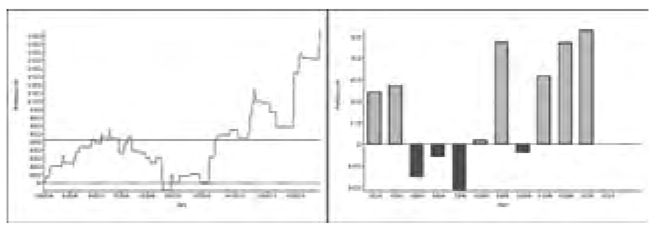

Figure 9: Efficiency of Kalman filter model 4 to detect trends.

Discussion

Parameters for the Kalman filter models are obtained by a general optimization. Hence, they provide the best possible choice of parameters. Results presented here should be analyzed with this in mind.

We clearly see that models 1 and 2 provide similar results—about $20K of net profit for one year trading the E-mini contract. When adding the new feature of a short- and long-term model factor, we increase net profit to $29L, which is substantial. We reduce maximum drawdown from -$7,300 USD to -$3,800 USD. This is a material gain. Model 4 performs even better, as we generate an additional $10K, with net profit skyrocketing to $40K USD, with a further reduction of drawdown to -$2,600 USD.

Table 7: Trades list for Kalman model 4.

Trade	Direct ion	Ent ry dat e	Entry price	Exit dat e	Exit price	Profit	PnL	Commission	Days in posit ion
1	Long	Mar-31-15	2,043	Apr-01-15	2033.5	(454.0)	(454.0)	4	2
2	Short	Apr-01-15	2,034	Apr-02-15	2026	371.0	(83.0)	4	2
3	Long	Apr-02-15	2,026	Apr-08-15	2045.25	958.5	875.5	4	4
4	Short	Apr-08-15	2,045	Apr-09-15	2047.5	(116.5)	759.0	4	2
5	Long	Apr-09-15	2,048	Apr-10-15	2061.5	696.0	1,455.0	4	2
6	Short	Apr-10-15	2,062	Apr-21-15	2076.25	(741.5)	713.5	4	8
7	Long	Apr-21-15	2,076	Apr-22-15	2069.75	(329.0)	384.5	4	2
8	Short	Apr-22-15	2,070	May-04-15	2081.75	(604.0)	(219.5)	4	9
9	Long	May-04-15	2,082	May-05-15	2079.75	(104.0)	(323.5)	4	2
10	Short	May-05-15	2,080	May-07-15	2048.25	1,571.0	1,247.5	4	3
11	Long	May-07-15	2,048	May-11-15	2084.75	1,821.0	3,068.5	4	3
12	Short	May-11-15	2,085	Jun-10-15	2062.25	1,121.0	4,189.5	4	23
13	Long	Jun-10-15	2,062	Jun-11-15	2083.5	1,058.5	5,248.0	4	2
14	Short	Jun-11-15	2,084	Jul -01-15	2054.25	1,458.5	6,706.5	4	15
15	Long	Jul -01-15	2,054	Jul -03-15	2049.75	(229.0)	6,477.5	4	3
16	Short	Jul -03-15	2,050	Jul -10-15	2050.5	(41.5)	6,436.0	4	6
17	Long	Jul -10-15	2,051	Jul -14-15	2074.5	1,196.0	7,632.0	4	3
18	Short	Jul -14-15	2,075	Jul -29-15	2071	171.0	7,803.0	4	12
19	Long	Jul -29-15	2,071	Jul -30-15	2077.5	321.0	8,124.0	4	2
20	Short	Jul -30-15	2,078	Aug-24-15	1851.25	11,308.5	19,432.5	4	18
21	Long	Aug-24-15	1,851	Aug-28-15	1960	5,433.5	24,866.0	4	5
22	Short	Aug-28-15	1,960	Sep-02-15	1921.25	1,933.5	26,799.5	4	4
23	Long	Sep-02-15	1,921	Sep-10-15	1920.25	(54.0)	26,745.5	4	7
24	Short	Sep-10-15	1,920	Sep-11-15	1928.25	(404.0)	26,341.5	4	2
25	Long	Sep-11-15	1,928	Sep-17-15	1974.75	2,321.0	28,662.5	4	5
26	Short	Sep-17-15	1,975	Sep-21-15	1948.5	1,308.5	29,971.0	4	3
27	Long	Sep-21-15	1,949	Oct-06-15	1967.5	946.0	30,917.0	4	12
28	Short	Oct-06-15	1,968	Oct-15-15	1986.25	(941.5)	29,975.5	4	8
29	Long	Oct-15-15	1,986	Oct-19-15	2010.25	1,196.0	31,171.5	4	3
30	Short	Oct-19-15	2,010	Dec-15-15	2031	(1,041.5)	30,130.0	4	42
31	Long	Dec-15-15	2,031	Dec-16-15	2048.25	858.5	30,988.5	4	2
32	Short	Dec-16-15	2,048	Dec-22-15	2022.75	1,271.0	32,259.5	4	5
33	Long	Dec-22-15	2,023	Dec-23-15	2043	1,008.5	33,268.0	4	2
34	Short	Dec-23-15	2,043	Jan-11-16	1924.5	5,921.0	39,189.0	4	12
35	Long	Jan-11-16	1,925	Jan-14-16	1890	(1,729.0)	37,460.0	4	4
36	Short	Jan-14-16	1,890	Jan-15-16	1862	1,396.0	38,856.0	4	2
37	Long	Jan-15-16	1,862	Jan-18-16	1869.5	371.0	39,227.0	4	2
38	Short	Jan-18-16	1,870	Jan-19-16	1894	(1,229.0)	37,998.0	4	2
39	Long	Jan-19-16	1,894	Jan-26-16	1878.5	(779.0)	37,219.0	4	6
40	Short	Jan-26-16	1,879	Jan-27-16	1890.25	(591.5)	36,627.5	4	2
41	Long	Jan-27-16	1,890	Jan-28-16	1894	183.5	36,811.0	4	2
42	Short	Jan-28-16	1,894	Jan-29-16	1894.5	(29.0)	36,782.0	4	2
43	Long	Jan-29-16	1,895	Feb-02-16	1913.5	946.0	37,728.0	4	3
44	Short	Feb-02-16	1,914	Feb-04-16	1901.5	596.0	38,324.0	4	3
45	Long	Feb-04-16	1,902	Feb-17-16	1906	221.0	38,545.0	4	10
46	Short	Feb-17-16	1,906	Feb-25-16	1931.25	(1,266.5)	37,278.5	4	7
47	Long	Feb-25-16	1,931	Feb-26-16	1959.75	1,421.0	38,699.5	4	2
48	Short	Feb-26-16	1,960	Feb-26-16	1942.5	858.5	39,558.0	4	1

Conclusion

In this paper, we empirically validate that Kalman filters with meaningful dynamics have predictive power. After reviewing moving averages and the general equation for its lag at order n with respect to the one at the first order, we examine four Kalman filter models: the common one with speed and acceleration concepts, the traditional statistical one referred to as the local linear trend, a new model that splits price contribution between short- and long-term effect, and a last one that encompasses all above with an additional term corresponding to the position of the price with regard to its extremums. We find empirically that model 4 performs far better than any other models. We also confirm that KF models have zero lag and capture price dynamic better than previous combinations of moving averages, like DEMA or TEMA. We confirm on model 4 that oscillators and trend-following indicators are a powerful combination that performs better than any single indicators.

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Wrestling With a Grizzly Bear: An Argument Against Pure Buy and Hold Investing

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Abstract

This paper investigated the feasibility of using a trend-trading model on U.S. equities over the time period of 1929–2009 to manage risk and aid in investment decisions. To do so, three secular bear and two secular bull markets were analyzed, and a strategy, based on a weekly Relative Strength Index (RSI) indicator, is applied.

The backtest results provide evidence that using the RSI (14) indicator as a trend-trading strategy helps accomplish the following: 1) Generates profits in excess of a simple buy and hold strategy during a secular bear market; 2) Reduces downside risk versus buy and hold caused by bear market cyclical drawdown periods; and 3) Underperforms buy and hold during a secular bull market.

Introduction

The strategy used in this study consists of two moving averages of the RSI, and the usual crossover rules are applied. A long indication from the indicator translates into a position consisting of a total investment. A short indication is interpreted as a period where no investments are held. The results are compared to a buy and hold strategy.

The research herein has provided an argument against pure buy and hold investing, especially during a secular bear market. Historically, buy and hold tends to merely produce the flat-to-lower returns associated with the overall markets during these turbulent time periods. Employing a buy and hold strategy during a secular bear market is like wrestling with a grizzly bear; it can be potentially lethal, especially to a portfolio.

Trend Trading in Bull and Bear Markets

Technical analysts have relied on the assumption that there lies the ability to predict market returns by identifying patterns and characteristics of past stock market prices. One method of identifying price patterns is by understanding the price trend within various "bull" and "bear" markets and applying a technical trend-trading strategy for buy and sell decisions. Historically, trend-trading strategies have been applied to commodities, futures, and currency markets; they seek to enter the market in the direction of an existing trend and to exit when the trend reverses.[1] Over the past decade, limited research has been published regarding trend-trading strategies as applied to U.S. equities markets. In their book *The Ivy Portfolio: How to Invest Like the Top Endowments and Avoid Bear Markets*, Faber and Richardson provide evidence that a moving average–based, trend-trading strategy applied within U.S. equities can generate profitable outcomes.[2]

Most investors associate the application of a trend-trading strategy to take advantage of price momentum generated in a bull market; however, another important application of trend trading is the protection of assets during a painful bear market drawdown.

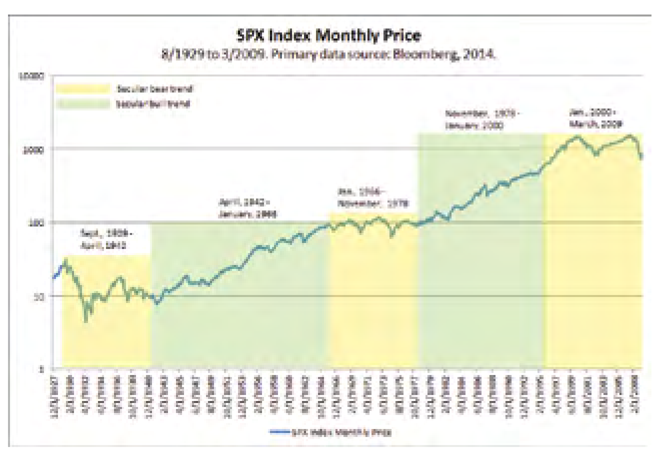
Secular Market Trends

According to Martin Pring,[3] a secular trend is a long-term trend constructed from a number of primary or cyclical trends and secondary trends. A secular trend typically lasts 10 to 25 years in duration. For example, a secular bear market comprises smaller magnitude bull markets and larger bear markets, and a secular bull market comprises larger bull markets and smaller bear markets.

For the purposes of this paper the following terms are further clarified: Bull and bear markets are defined as upward and downward market trends, respectively. Using technical analysis, a bull market can be represented on a line chart as the price generally moving higher, exhibiting characteristics of higher-highs and higher-lows. Conversely, a bear market can be represented directionally as the price generally moving lower (and in some cases sideways), exhibiting characteristics of lower-highs and lower-lows.

The period from 1929–2009 for U.S. equities can be divided into three secular bear and two secular bull markets. The secular bear markets lasted for 13 (1929–1942), 12 (1966–1978), and 9 (2000–2009) years, respectively. The secular bull markets lasted for 24 (1942–1966) and 22 (1978–2000) years, respectively. Please note that the timeframe of 1966–1978 reflects the secular bear trend on the S&P 500; for the Dow Jones Industrial Average, it did not finish its secular bear trend until four years later in 1982. For the scope of this research, it is assumed that the March 6, 2009, bottom on the S&P 500 Index constitutes an end to the most recent secular bear market (Figure 1).

Figure 1. The S&P 500 secular markets from 1929–2009



The Relative Strength Index (RSI) as an Oscillator

The RSI is a technical indicator invented by J. Welles Wilder and documented in his 1978 book, *New Concepts in Technical Trading Systems*.[4] The RSI indicator is one of the most popular technical analysis indicators available to users and is commonly found as a default internal indicator to many technical analysis software packages. The RSI is calculated on the basis of the speed and direction of a stock or index's price movement. It measures the stock or index's internal strength by comparing the magnitude of recent gains to recent losses. A common look-back period for the RSI is 14 trading periods, which then becomes the popular RSI (14) indicator. The RSI (14) calculation is found in Equation 1 below, whereby the ratio of the average gains/average losses over the prior 14 trading periods is known as the Relative Strength (RS). The RS is calculated into the RSI (14) as a normalized index (between 0 and 100) through the second part of Equation 1.

Equation 1. The RSI (14) calculation

$$RS = \frac{(Average\_of\_14\_periods\_closes\_UP)}{(Average\_of\_14\_periods\_closes\_DOWN)}$$

$$RSI_{14} = 100 - \frac{(100)}{(1+RS)}$$

The RSI as a Trend Trading Indicator

Although Wilder created the RSI (14) indicator, Andrew Cardwell is recognized today by many technical analysts as a leading authority on the RSI (14). Cardwell's research on the indicator has "opened the door to new methods of using oscillators in general for trend following and price projection."[5] Cardwell employs two moving averages, which smooth the RSI (14) values: the 9-period simple moving average (SMA) and the 45-period exponential moving average (EMA). When used together, these two moving averages help diagnose RSI (14) trend direction.[6]

In *RSI: The Complete Guide* (2004), John Hayden suggests that to confirm a bullish RSI (14) trend, the 9-period RSI (14) SMA must cross above the 45-period RSI (14) EMA.[7] Further, Walter Baeyens, in *RSI: Logic, Signals & Time Frame Correlation* (2007), discusses the importance of using Cardwell's application of 9-period SMA and 45-period EMA crossovers on both price and RSI (14) to confirm buy-and-sell signals.[8]

The 9-period SMA calculation is defined by Equation 2, and the 45-period EMA is defined by Equation 3.

Equation 2. The RSI (14) nine period simple moving average calculation

$$\frac{\left(\sum_{n=1}^{9} RSI(14_{close})\right)}{9}$$

Equation 3. The RSI(14) 45-period exponential moving average calculation

$$EMA_{Today} = a * [(RSI(14_{cp})) - (RSI(14_{EMA\_pp}))] + [(RSI(14_{EMA\_pp}))]$$

Where:

a = Acceleration Factor (or, 2 / (No. of period's EMA + 1) cp = current period's RSI (14) close value. EMA pp = previous periods RSI (14) EMA value.

A Modified Use of the RSI Trend Trading Indicator

The RSI (14) trend-trading model proposed in this paper is a moving-average-based trading system. Cardwell's extensive research on the RSI (14) provides evidence that using two moving averages, one short-term (9-period SMA) and one longer-term (45-period EMA), is useful in assessing trend direction. The RSI (14) trend-trading model is based on the application of the 9-period SMA and 45-period EMA compared against the RSI (14) line. Cardwell and other published research suggest that trade signals are generated after a 9-period SMA versus 45-period EMA crossover takes place. The RSI (14) model herein will be original, in that it creates trade signals after the RSI (14) line moves either completely above or below both the short- and long- term moving averages (Figure 2). An investor will be long the market when the RSI (14) line is above both the 9- and 45-period moving averages; and will be out of the market when the RSI (14) line is below both the moving averages.

Figure 2. An example buy signal using the RSI (14) weekly line chart with 9- and 45-period moving averages

There is a limited amount of research in the technical analysis publications regarding using the RSI (14) trend trading indicator. In the *IFTA Journal*, 2015 edition, David Price[9] published research titled "Enhancing Portfolio Returns and Reducing Risk by Utilizing the Relative Strength Index as a Market Trend Identifier". Mr. Price's research, although similar in that it is primarily based on the RSI indicator, is different in application and methodology to that proposed in this paper.

To date, I have not found any published research on this specific application of the RSI (14) line crossing through both moving averages as a buy-sell trend-trading strategy. Though this strategy is a derivative of Wilder and Cardwell's research, it is unique in its application.

Research Objective

The objective of this paper is therefore to examine the efficacy of using the RSI (14) as a trend trading indicator that could be used in a systematic way to improve profits and reduce risk compared with pure buy and hold, by reducing the portfolio's exposure to the market during more turbulent and volatile bear market periods.

Materials and Methods

Methodology for RSI (14) Trend-Trading Identifier Backtest

To test the hypothesis that the RSI (14) can be utilized as a trend-trading indicator, and whether its readings provide an investment approach that increases profitability and reduces risk, the strategy is backtested against the S&P 500 Index—the U.S. stock market index of the 500 leading companies by market capitalization.

The following criteria allow this model to be simple, yet emotion-free and objective.

1. The model uses purely mathematical logic.
2. The same model and parameters can be used for various time periods (e.g., minute, daily, weekly, monthly) based on the user's time horizon.

The RSI (14) trend-trading methodology includes the following:

Initial Entry

BUY RULE: Enter long when the RSI (14) line closes above the 9-period SMA and above the 45-period EMA.

SELL RULE: Enter cash when the RSI (14) closes below the 9-period RSI (14) SMA and below the 45-period RSI (14) EMA.

Ongoing

A. If long, enter cash when the RSI (14) closes below both the 9-period SMA and 45-period EMA.
B. If cash, enter long when the RSI (14) closes above both the 9-period SMA and 45-period EMA.

Additional rules:

- For the purposes of this report, the test data analysis only considers this model as a long-cash model. It is important to note that the model can also support a long-short strategy.
- The data analysis is based on a weekly period; this is targeted for intermediate-term (9–12 month) time horizon investors. Some mechanics of the model are as follows: If the RSI (14) closed above both 9- and 45-period moving averages on a Friday, then due to the weekly frequency, the following Friday's close is when the trade would be entered/exited, thereby creating a time lag in processing in order to simulate real-time trade processing requirements.
- For the secular bear market 2000–2009, the data output are total return series that include dividends.
- For the secular bear markets 1929–1942 and 1966–1978, the data output are price return series.
- For the secular bull markets 1942–1966 and 1978–2000, the data output are price return series.
- Cash returns were not calculated; the assumption was that the investor was out of the market.
- Taxes are excluded.
- Transaction costs are included.
- RSI (14) weekly closing data are obtained through FactSet Research Systems and Bloomberg, L.P. Data are analyzed using Microsoft Excel 2007.

The backtest for each secular trend scenario was made with a theoretical starting balance of US $1 million. This would be a reasonable amount for a registered investment advisor to invest in as a large cap asset allocation to a portfolio.

The overall time period for backtests include three secular bear and two secular bull markets applied to the S&P 500 Index from 1929–2009. The specific dates for each backtest scenario are as follows:

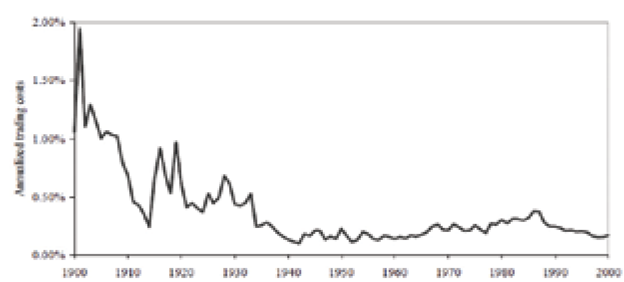
Secular bear trend scenarios:
9/6/1929–4/28/1942
1/14/1966–11/17/1978
1/14/2000–3/6/2009

Secular bull trend scenarios:
4/28/1942–1/14/1966
11/17/1978–1/14/2000

Transaction Costs

For each scenario backtest, transaction costs are included to represent the variable friction in trading U.S. equities over the past 80 years. Transaction costs including bid-ask spreads plus commissions going from 1900–2000 are represented in Figure 3.

Figure 3. Estimated annualized trading costs of NYSE stocks 1900–2000 (= turnover * [bid-ask half spread + one-way commission]) (Adapted from Charles M. Jones[10])



Results

RSI (14) Model Backtest Results: Three Secular Bear Markets

The test results of the RSI (14) trend-trading model applied within a secular bear market are compelling. Not only does the timing model outperform buy and hold for each time period studied, but it also protects the investor from a significant drawdown due to an extreme market event.

The first test case analyzes the results of all three secular bear markets combined (a total of 34 years). Figure 4 illustrates the test results, which include annual performance of the RSI

(14) trend model compared with buy-and-hold for the S&P 500 Index. The model generated fewer large percent losses and fewer large percent gains compared with buy and hold, which is supportive of reducing fat-tail or higher-risk events. The test results summary statistics in Table 1 reveal the following benefits of using the model compared with buy and hold: 1) a higher average or mean return; 2) a lower standard deviation or overall less risk; 3) a more positive skewness than buy-and-hold (meaning the asymmetric tail extends toward more positive annual returns); 4) a higher kurtosis value, suggesting that there was a peak of distribution in the return stream, which in this case is supportive of more stable returns with less tail risk; and 5) lower minimum annual return values than buy-and-hold, and added downside risk protection.

The test results suggest that the RSI (14) model protects the investor by avoiding extreme unexpected bear market losses. The mechanics of the model will execute a move to cash when the RSI (14) indicator triggers a sell signal, thus eliminating any extreme fat tail losses associated with the buy and hold strategy.

Figure 4. Yearly percent returns in three secular bear markets

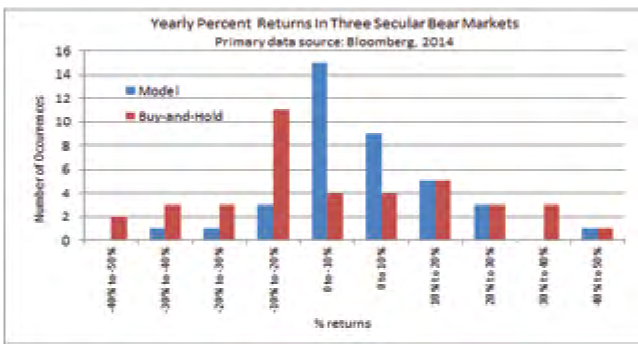


Table 1. Performance statistics for three secular bear markets

	RSI(14) Model	Buy-and-Hold
Average	1.10%	-3.26%
Median	-0.11%	-5.18%
Standard Deviation	17.63%	23.24%
Kurtosis	0.98	-0.61
Skewness	0.61	0.21
Minimum	-35.71%	-47.07%
Maximum	48.24%	45.97%

Primary data source: Bloomberg, 2014

Regarding model performance, the results show that the RSI (14) model outperformed buy and hold for each of the three secular bear markets, on average by 39.20% (Table 2). The outperformance versus buy and hold can be attributed to the elimination of the high-risk fat tail outliers, thus avoiding major market losses. The model provided greater downside risk protection compared with buy and hold, based on the following:

- On average over the three time periods, the RSI (14) model's maximum drawdown was 14.21% better than buy and hold, and its standard deviation was 6.11% lower than buy and hold, which is an indication of lower risk.

Table 2. Performance of the RSI (14) model compared to buy and hold for three secular bear markets

SECULAR BEAR MARKET	Returns: RSI (14) Model	S&P 500 Buy-and-Hold	Relative Performance
1/14/2000 to 3/6/2009			
Performance	-32.88%	-52.60%	19.72%
MAX Drawdown	-19.54%	-38.49%	
Best Year	26.25%	26.38%	
Standard Deviation	12.38%	19.92%	
1/14/1966 - 11/17/1978			
Performance	61.77%	2.14%	59.63%
MAX Drawdown	-17.39%	-29.72%	
Best Year	29.69%	31.55%	
Standard Deviation	13.02%	17.72%	
9/6/1929 - 4/28/1942			
Performance	-17.40%	-76.40%	59.00%
MAX Drawdown	-35.71%	-47.07%	
Best Year	48.24%	45.97%	
Standard Deviation	23.79%	29.87%	

Primary data source: Bloomberg, 2014

AVE = 6.11% lower than Buy and Hold

AVE = 14.20% better than Buy and Hold

AVE = 39.20% outperformance compared with Buy and Hold

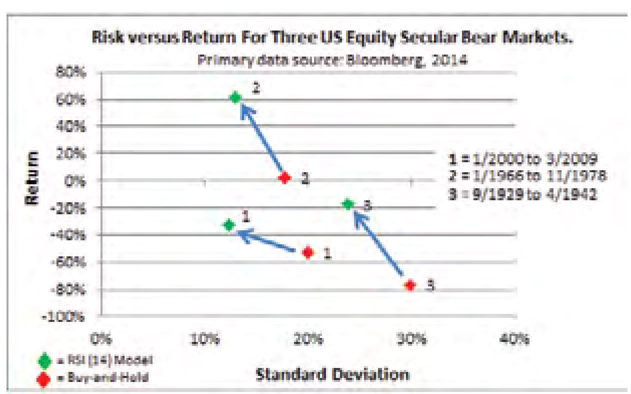
Adjusting for transaction or frictional trading costs is provided in Table 3. Transaction costs include bid–ask spreads and commissions. The transaction costs in the 1929–1942 timeframe were the highest, at 0.82% per round trip trade (i.e., includes both the buy and sell) of the three secular bear markets studied, resulting in a 20.6% drag on relative performance. The 1966–1978 secular bear market had average costs per trade at 0.44% and resulted in a 13.7% drag on relative performance. The 2000–2009 secular bear market had the lowest transaction costs per trade at 0.18% and resulted in a drag on relative performance of only 5.5%.

Table 3. Performance with transaction costs for three secular bear markets

SECULAR BEAR MARKET	Returns: RSI (14) Model	ADJ for TXN Costs	S&P 500 Buy-and-Hold	Adjusted Relative Performance	Transaction Cost: Average Per Round Trip Trade
1/14/2000 to 3/6/2009					
Performance	-32.88%	-37.93%	-52.60%	14.67%	-0.18%
1/14/1966 - 11/17/1978					
Performance	61.77%	48.07%	2.14%	45.93%	-0.44%
9/6/1929 - 4/28/1942					
Performance	-17.40%	-38.02%	-76.40%	38.38%	-0.82%

Primary data source: Bloomberg, 2014

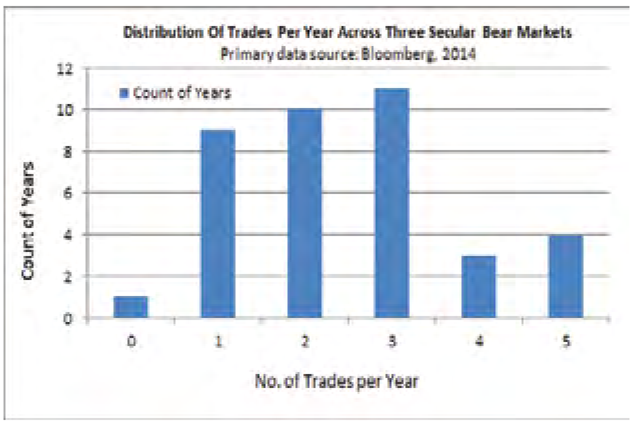
Figure 5. Risk and return statistics for three secular bear markets



In addition, the test results identify that the risk (average standard deviation) versus return (overall performance) characteristics of the RSI (14) model are more attractive than buy-and-hold for all three secular bear markets (Figure 5). For each of the secular bear markets studied, the results showed that the RSI (14) model had higher overall return and lower standard deviation compared with buy-and-hold.

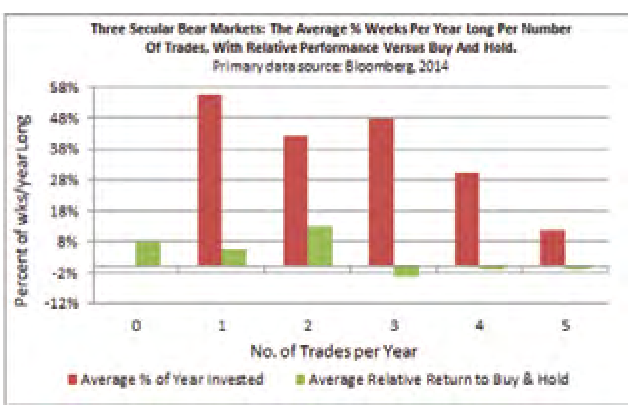
The next test case analyzes the trade data generated by the model. The RSI (14) model triggers either a buy or sell trade based on the timing rules. Figure 6 shows the distribution of the number of trades generated for all three secular bear markets. The chart is showing a distribution with the most prominent number of trades per year focused in the 1–3 range. (Note: Each trade includes both a buy and a sell transaction. As an example: two trades = two buys and two sells.)

Figure 6. The distribution of number of trades per year for the RSI (14) model for three secular bear markets



As with any trend-trading model, there will be times when the investor is not in the market, based on the model's signal. The rules employed by the RSI (14) model assume the investor is either in the market (long) or out (cash). Figure 7 illustrates the average percentage of weeks per year that the investor is long for each number of trades per year, along with the average relative return.

Figure 7. The average percent weeks invested by the RSI (14) model by number of trades with relative performance compared to buy and hold for three secular bear markets



The test results across the three secular bear markets suggest that for years with trades less than or equal to two, the model was invested less than 55% of the year, and in these cases, outperformed buy and hold. As the trades per year increased to three or more, the model's relative performance suffered, which may be caused by potential trade whipsaw activity or false signals generated by the model. In the case of four trades or more per year, the investor was still only long, on average, 20.9% of the time for approximately 7 out of 34 (20.5 %) of the secular years studied.

RSI (14) Model Backtest Results: Two Secular Bull Markets

The test results of the RSI (14) trend-trading model applied within a secular bull market are not compelling. In both scenarios, the trend-trading model could not outperform buy and hold for each time period studied. The test results confirm that in a bull market, buy and hold has an advantage, mainly due to fact that the trend-trading model is at times not fully invested in the market and additionally incurs frictional trading costs, as opposed to buy and hold, which is in the market 100% of the time and incurs no trading costs.

The first test case analyzes the results of two secular bull markets combined, 1942–1966 and 1978–2000, with a total of 46 years. Figure 8 illustrates the test results, which include annual performance of the RSI (14) trend model compared with buy and hold for the S&P 500 Index. The model generated fewer large percent losses and fewer large percent gains compared with buy and hold, which is supportive of reducing fat-tail or higher-risk events. The test result summary statistics in Table 4 reveal the following when using the model compared with buy and hold in a secular bull market: 1) a lower average or mean return; 2) a lower standard deviation or overall less risk; 3) the distribution of % returns for the model shifted to the left in comparison with buy and hold (Figure 8), meaning buy and hold returned better performance on average; and 4) the model returned lower minimum values than buy-and-hold, which added downside risk protection, however, lower maximum annual returns than buy and hold, which restricted upside potential (Table 4 and Table 5).

Figure 8. Yearly percent returns in two secular bull markets

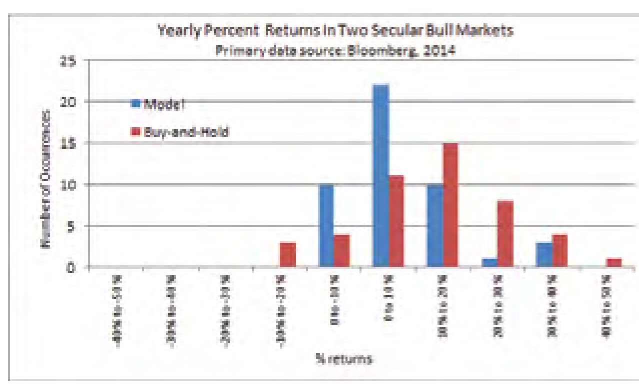


Table 4. Performance statistics for two secular bull markets

	RSI(14) Model	Buy-and-Hold
Average	6.69%	12.14%
Median	4.89%	12.69%
Standard Deviation	10.65%	13.92%
Kurtosis	1.18	-0.50
Skewness	1.01	0.07
Minimum	-9.39%	-14.31%
Maximum	39.31%	45.02%

Primary data source: Bloomberg, 2014

The backtest results reveal that the RSI (14) model underperformed buy and hold for both secular bull markets, on average by 871.15% (Table 5). However, on average over the two time periods, the RSI (14) model's maximum drawdown was 3.13% better than buy-and-hold, and the standard deviation was 3.31% lower than buy and hold, which is an indication of lower risk.

Table 5. Performance of the RSI (14) model compared to buy and hold for two secular bull markets

SECULAR BULL MARKET	Returns: RSI (14) Model	Returns: S&P 500 Buy-and-Hold	Returns: Relative Performance
11/17/1978 to 1/14/2000			
Performance	222.00%	1363.67%	-1141.67%
MAX Drawdown	-5.62%	-6.56%	
Best Year	30.44%	34.11%	
Standard Deviation	9.51%	12.54%	
4/28/1942 - 1/14/1966			
Performance	457.50%	1058.13%	-600.63%
MAX Drawdown	-8.99%	-14.31%	
Best Year	39.30%	45.02%	
Standard Deviation	11.71%	15.30%	

Primary data source: Bloomberg, 2015

AVE = 3.31% lower than Buy and Hold

AVE = 3.13% better than Buy and Hold

AVE = 871.15% underperformance compared with Buy and Hold

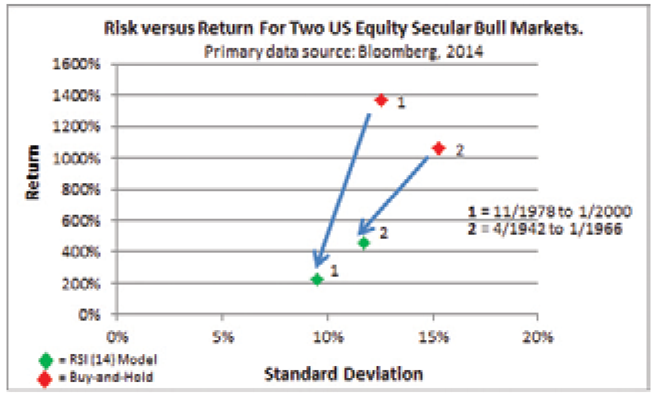
Transactional costs associated with using a trend-trading model in a secular bull market are damaging to the overall performance versus buy and hold. Adjusting for the model transaction or frictional trading costs is provided in Table 6. Transaction costs include bid–ask spreads and commissions. The transaction costs for both secular bull markets were, on average, at 0.54% per round trip trade (i.e., including buy and sell trades together). The transactional costs resulted in a 29.15% drag on relative performance for the period of 1942–1966 and a 34.40% drag on relative performance for the period of 1978–2000.

Table 6. Performance with transaction costs for two secular bull markets

SECULAR BULL MARKET	Returns: RSI (14) Model	Returns: ADJ for TXN Costs	Returns: S&P 500 Buy-and-Hold	Returns: Adjusted Relative Performance	Transaction Cost: Average Per Round Trip Trade
11/17/1978 to 1/14/2000					
Performance	222.00%	187.60%	1363.67%	-1176.07%	-0.54%
4/28/1942 - 1/14/1966					
Performance	457.50%	428.35%	1058.13%	-629.78%	-0.54%

Primary data source: Bloomberg, 2014

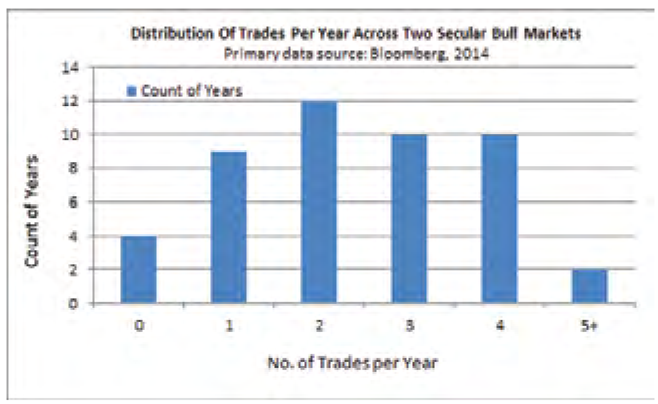
Figure 9. Risk and return statistics for two secular bull markets



The risk (standard deviation) versus return (overall performance) characteristics of using the RSI (14) model in a secular bull market show that there is a cost to be paid for added protection (Figure 9). For both secular bull markets studied, the results showed that the RSI (14) model had lower standard deviation than buy and hold; however, the tradeoff was that the overall return was also lower compared to buy and hold.

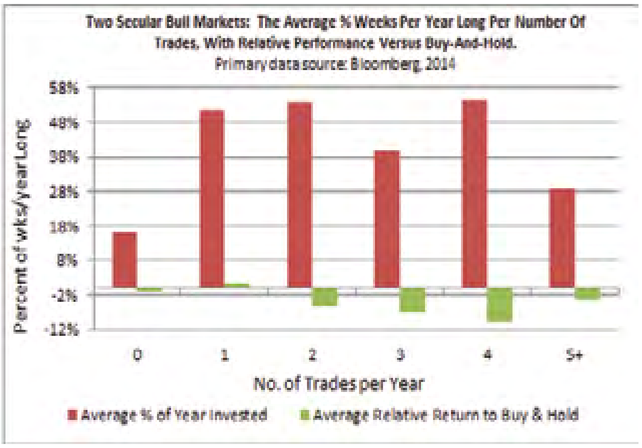
The next test case analyzes the trade data generated by the model. The RSI (14) model triggers either a buy or sell trade based on the timing rules. Figure 10 shows the distribution of number of trades generated for both secular bull markets. The chart shows a distribution with the most prominent number of trades per year focused in the 2–4 range; which is higher than the secular bear market cases studied.

Figure 10. The distribution of the number of trades per year for the RSI(14) model for two secular bull markets



As with any trend-trading model, there will be times when the investor is not in the market, based on the model's signal. The rules employed by the RSI (14) model assume the investor is either in the market (long) or out (cash). Figure 11 illustrates the average percentage of weeks per year that the investor is long for each number of trades per year, along with the average relative return.

Figure 11. The average percent invested by the RSI (14) model by number of trades with relative performance compared to buy and hold for two secular bull markets

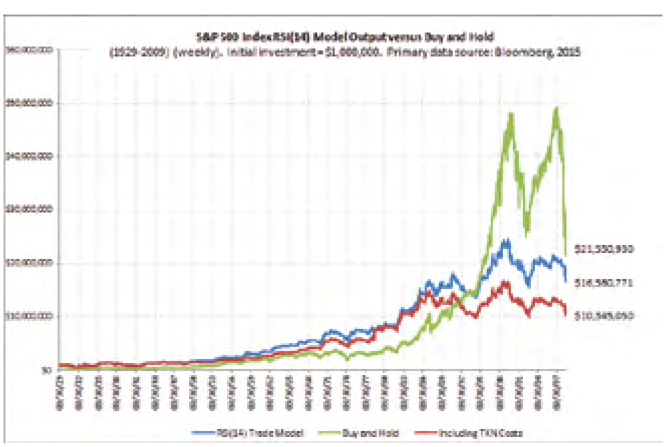


The test results across the two secular bull markets suggest that for years with trades equal to one, the model was invested less than 52% of the year, and in these cases, outperformed buy and hold. In all other cases, the model underperformed buy and hold.

RSI (14) Model Backtest Results: 1929–2009, U.S. EQUITIES (S&P 500)

As can be seen in Figure 12, the RSI (14) model applied to the S&P 500 Index underperformed the buy and hold approach for the period 1929–2009. Breaking it down into secular markets, the model tended to outperform buy in hold for the three secular bear markets studied; however, it underperformed buy and hold during the two secular bull market time periods. Transactional friction dragged down the model throughout the entire time series; looking at the last data point on Figure 12, the transaction effect on the model decreased performance by 37.6%, with an average cost per round trip trade at 0.54%. At the March 6, 2009, data point, the model had underperformed buy and hold by 23% and, including the transaction costs, had underperformed buy and hold by 52%. Over the 1929–2009 time periods, an initial investment of $1 million generated $16,580,771 for the RSI (14) model, $10,345,050 adjusted for transaction costs, and $21,550,930 for buy and hold.

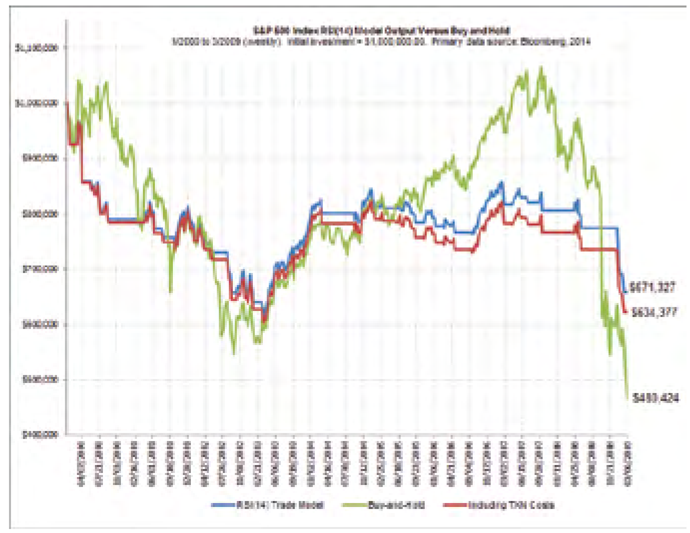
Figure 12. The RSI(14) model output with transaction costs compared to buy and hold for the period of 1929–2009



RSI (14) Model Backtest Results: Secular Bear Market From January 2000 to March 2009

Based on the test conducted, the RSI (14) model outperformed buy and hold by 19.79% during the most recent secular bear market, which began in January 2000 and lasted until March 2009 (Figure 13). Including transaction costs for 31 roundtrip trades (i.e., one buy and one sell), the RSI (14) model outperformed buy and hold by 14.67%. Over the 2000–2009 time periods, an initial investment of $1 million generated $671,327 for the RSI (14) model, $634,377 adjusted for transaction costs, and $480,424 for buy and hold.

Figure 13. The RSI (14) model output with transaction costs compared to buy and hold for the period of January 2000 to March 2009



One major contribution to the outperformance generated by the RSI (14) model was the ability to prevent losses during bear market drawdowns. For example, the RSI (14) model worked well at preventing losses during the following years (Table 7):

- For 2001, the annual return for the model was 2.84% versus buy and hold at -13.04%.
- For 2002, the maximum drawdown generated by the model was -16.20% compared to -24.22% for buy and hold.
- For 2008, the maximum drawdown for the model was -3.84% compared with -41.00% for buy and hold.
- From January 2009 to March 2009, the maximum drawdown for the model was -15.01% compared with -26.65% for buy and hold. Evidence of increased downside risk protection is provided in Table 7, depicted by the standard deviation metric. For the bear market period, the RSI (14) model's average standard deviation was 8.44% lower than buy and hold.

Table 7. Performance of the strategy for the 2000–2009 time period

Secular Bear Market (1/1/2000 - 3/6/2009)					RSI(14) Model	
	Returns				Trade Data	
Year	RSI (14) Model	S&P 500 Buy & Hold	Relative Performance	Year	No. of Trades	Weeks/Yr Invested (%)
1/1/2009-3/6/2009	-15.01%	-26.65%	11.64%	2009	2	29.47%
2008	-3.84%	-41.00%	37.16%	2008	2	11.51%
2007	-3.52%	4.20%	-7.72%	2007	3	45.75%
2006	4.76%	13.61%	-8.85%	2006	4	59.26%
2005	-5.96%	2.86%	-8.82%	2005	5	59.18%
2004	5.38%	9.20%	-3.82%	2004	3	48.77%
2003	21.76%	26.44%	-4.68%	2003	1	82.19%
2002	-16.20%	-24.22%	8.02%	2002	5	70.14%
2001	2.84%	-13.04%	15.88%	2001	3	33.70%
2000	-19.54%	-10.14%	-9.40%	2000	5	32.00%
				Total	31	
Combined Yearly Returns (%)				Trades		Wks/Yr Invested (%)
Average	-2.93%	-5.87%	2.94%	Average	3.1	47.20%
Median	-3.68%	-3.64%	-4.25%	Median	3	47.26%
Max	21.76%	26.44%	37.16%	Max	5	82.19%
Min	-19.54%	-41.00%	-9.40%	Min	1	11.51%
St. Dev	12.38%	20.82%	15.23%			
Batting Average	40.00%	50.00%	40.00%			
Overall Performance	-32.80%	-52.59%	19.79%			

Primary data source: Bloomberg, 2015

The RSI (14) model generated 31 sets of buy/sell trades for the January 2000 to March 2009 time period. The model's batting average for success against buy and hold was 32.26%, with an average trade return at -1.13% compared to buy and hold at -1.82%. Standard deviation for the model based on the trade data was lower at 6.60% compared to 10.82% for buy and hold. Max drawdown from the trades was better for the model at -12.61% compared to buy and hold at -34.57%. The model was long 47% of the time during the 2000–2009 time period (Table 8).

Table 8. Trading activity of the strategy for the 2000–2009 time period

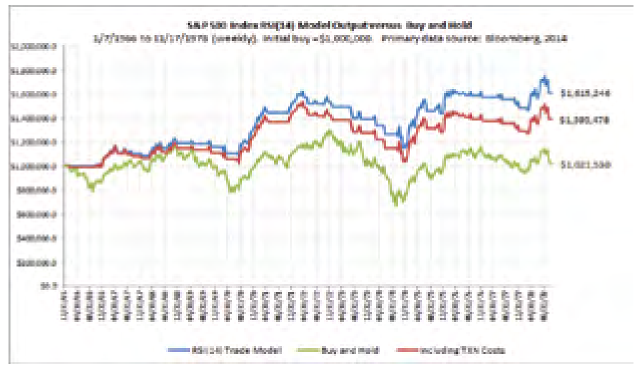
Buy Trades (Long)	Sell Trades (Cash)	RSI(14) Model Performance	Buy & Hold Performance	Relative Performance
01/14/2000	02/04/2000	-2.78%	4.25%	-7.03%
03/24/2000	04/20/2000	-6.08%	-4.62%	-1.47%
06/09/2000	06/30/2000	-0.16%	3.64%	-3.80%
07/14/2000	08/04/2000	-3.12%	-0.23%	-2.88%
08/25/2000	09/22/2000	-3.03%	-16.02%	12.99%
04/27/2001	06/22/2001	-2.21%	-5.02%	2.81%
08/10/2001	08/17/2001	-2.37%	-9.80%	7.44%
10/19/2001	02/15/2002	2.86%	8.46%	-5.60%
03/08/2002	04/19/2002	-3.36%	-6.91%	3.55%
05/24/2002	06/14/02	-7.06%	-15.48%	8.41%
08/30/2002	10/04/02	-12.61%	-2.01%	-10.60%
10/25/2002	01/31/2003	-4.67%	-3.80%	-0.87%
03/28/2003	03/15/04	27.91%	28.56%	-0.65%
09/24/2004	10/22/2004	-1.29%	5.05%	-6.34%
11/05/2004	01/28/2005	0.45%	3.36%	-2.91%
02/11/2005	03/18/2005	-1.30%	-0.77%	-0.53%
06/03/2005	07/01/2005	-0.13%	2.67%	-2.80%
07/15/2005	09/02/2005	-0.81%	0.81%	-1.62%
09/16/2005	10/14/05	-4.15%	0.84%	-4.98%
11/18/2005	01/06/2006	2.98%	3.15%	-0.17%
01/13/2006	01/27/2006	-0.30%	0.14%	-0.44%
02/24/2006	04/21/2006	1.69%	1.64%	0.05%
04/28/2006	05/19/2006	-3.33%	-1.18%	-2.14%
08/25/2006	03/16/07	7.09%	15.36%	-8.27%
04/27/2007	06/15/2007	2.60%	2.68%	-0.08%
07/20/2007	08/17/07	-5.79%	1.53%	-7.28%
10/05/2007	10/26/2007	-1.43%	-10.26%	8.82%
04/25/2008	05/30/2008	0.18%	-2.66%	2.84%
06/06/2008	06/13/2008	-0.05%	-34.57%	34.52%
01/09/2009	01/30/2009	-7.24%	-7.13%	-0.11%
02/13/2009	03/20/2009	-6.87%	-17.35%	10.48%
	Average	-1.13%	-1.82%	0.69%
	Median	-1.43%	-0.23%	-0.65%
	MAX	27.91%	28.56%	34.52%
	MIN	-12.61%	-34.57%	-10.60%
	St Dev	6.60%	10.82%	8.40%
	Batting Ave	25.81%	48.39%	32.26%
	Ave Winning Trade			9.19%
	Ave Losing Trade			-3.36%
	Number of Trades			31
	Percent Long			47%

Primary Data Source: Bloomberg, 2015

RSI (14) Model Backtest Results: Secular Bear Market From January 1966 to November 1978

The test results for the January 1966 to November 1978 secular bear market show that the RSI (14) model outperformed buy and hold by 59.63% (Figure 14). Including transaction costs for 31 roundtrip trades (i.e., one buy and one sell), the RSI (14) model outperformed buy and hold by 45.93%. Over the 1966–1978 time period, an initial investment of $1 million generated $1,615,246 for the RSI (14) model, $1,393,478 adjusted for transaction costs, and $1,021,530 for buy and hold.

Figure 14. The RSI (14) model output with transaction costs compared to buy and hold for the period of January 1966 to November 1978



As with the January 2000 to March 2009 secular bear market analysis, the majority of outperformance generated by the RSI (14) model from January 1966 to November 1978 was created by the prevention of losses. Test results show that the RSI (14) model prevented more losses compared with buy and hold during the following years: 1966, 1969, 1973, and 1974. The maximum drawdown for the RSI (14) model was -17.39% (1974) compared with -29.72% (1974) for buy and hold (Table 9).

Evidence of increased downside risk protection is provided in Table 9, depicted by the standard deviation metric. For the bear market period, the RSI (14) model's average standard deviation was 4.70% lower than buy and hold.

Table 9. Performance of the strategy for the 1966–1978 time period

Secular Bear Market (1/14/1966 - 11/17/1978)					RSI(14) Model	
	Returns				Trade Data	
Year	RSI (14)	S&P 500 Buy	Relative	Year	No. of	Weeks/Yr
1978	17.12%	-0.72%	17.84%	1978	1	55.77%
1977	-9.02%	-11.50%	2.48%	1977	3	30.77%
1976	12.90%	19.15%	-6.25%	1976	3	63.46%
1975	29.69%	31.55%	-1.88%	1975	2	65.38%
1974	-17.39%	-29.72%	12.33%	1974	3	25.00%
1973	-8.33%	-17.17%	8.84%	1973	3	21.15%
1972	8.65%	15.63%	-6.98%	1972	3	67.31%
1971	12.00%	10.79%	1.21%	1971	1	36.54%
1970	10.20%	0.10%	10.10%	1970	2	69.23%
1969	-6.90%	-11.36%	4.46%	1969	2	17.31%
1968	1.33%	7.66%	-6.33%	1968	3	69.23%
1967	11.20%	20.10%	-8.90%	1967	3	63.46%
1966	-2.67%	-13.10%	10.43%	1966	2	26.92%
				Total	31	
Combined Yearly Returns (%)				Trades		Wks/Yr Invested (%)
Average	4.52%	1.63%	2.89%	Average	2.3	47.04%
Median	8.65%	0.10%	2.48%	Median	3	55.77%
Max	29.69%	31.55%	17.84%	Max	3	69.23%
Min	-17.39%	-29.72%	-8.90%	Min	1	17.31%
St. Dev	13.02%	17.72%	8.62%			
Batting Average	61.54%	53.85%	61.54%			
Overall Performance	61.77%	2.14%	59.63%			

Primary data source: Bloomberg, 2015

The RSI (14) model generated 31 sets of buy/sell trades for the January 1966 to November 1978 time period. The model's batting average for success against buy and hold was 54.84%, with an average trade return at 2.23% compared to buy and hold at 1.34%. Standard deviation for the model based on the trade data was modestly lower at 10.17% compared to 11.14% for buy and hold. Maximum drawdown from the trades was better for the model at -7.50% compared to buy and hold at -20.83%. The model was long 47% of the time during the 1966–1978 time period (Table 10).

Table 10. Trading activity for the strategy during the 1966–1978 time period

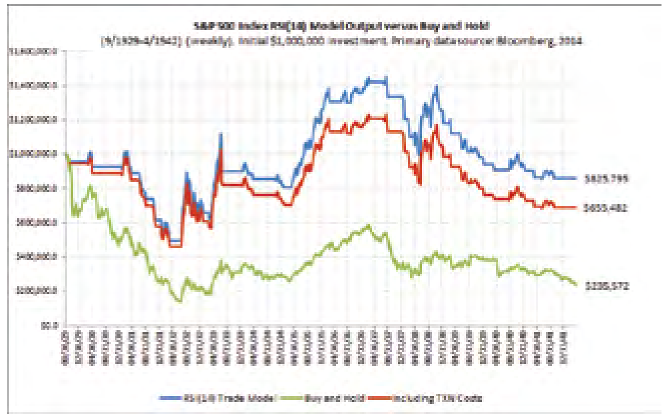
Buy Trades (Long)	Sell Trades (Cash)	RSI(14) Model Performance	Buy & Hold Performance	Relative Performance
01/14/66	02/25/66	-2.52%	-13.79%	11.27%
11/04/66	06/09/67	13.30%	16.30%	-3.00%
07/21/67	09/01/67	-0.38%	3.15%	-3.53%
09/22/67	10/27/67	-2.10%	-1.09%	-1.01%
01/05/68	01/26/68	-2.60%	0.61%	-3.21%
04/12/68	06/02/68	1.00%	4.49%	-3.49%
09/13/68	01/03/69	3.00%	4.15%	-1.15%
05/09/69	06/06/69	-2.00%	-6.60%	4.60%
10/24/69	11/28/69	-5.00%	-8.00%	3.00%
03/06/70	04/24/70	-7.50%	-13.00%	5.50%
07/24/70	06/04/71	31.00%	28.84%	2.16%
12/17/71	05/26/72	10.50%	9.45%	1.05%
06/02/72	06/16/72	-1.25%	2.00%	-3.25%
08/11/72	09/15/72	-2.80%	1.59%	-4.39%
11/10/72	01/03/73	5.50%	5.13%	0.37%
01/12/73	01/30/73	-2.80%	-10.74%	7.94%
08/03/73	08/24/73	-4.50%	1.82%	-6.32%
09/28/73	11/02/73	-1.25%	-8.44%	7.19%
03/15/74	04/05/74	-6.00%	-8.04%	2.04%
06/14/74	06/28/74	-5.50%	-20.83%	15.33%
10/18/74	12/13/74	-7.00%	0.46%	-7.46%
01/10/75	07/10/75	31.00%	30.50%	0.50%
10/17/75	12/12/75	-1.00%	2.31%	-3.31%
01/02/76	06/18/76	14.50%	14.10%	0.40%
06/25/76	08/13/76	0.51%	2.46%	-1.95%
09/17/76	10/01/76	-1.90%	1.12%	-3.02%
12/31/76	01/21/77	-3.00%	-5.83%	2.83%
06/24/77	08/05/77	-2.40%	-5.79%	3.39%
11/18/77	01/06/78	-3.90%	-6.26%	2.36%
03/24/78	10/13/78	17.12%	5.66%	11.46%
11/17/78				
	Average	2.23%	1.34%	1.24%
	Median	-1.90%	1.59%	0.45%
	MAX	31.00%	30.50%	15.33%
	MIN	-7.50%	-20.83%	-7.46%
	St Dev	10.17%	11.14%	5.44%
	Batting Ave	32.26%	58.06%	54.84%
	Ave Winning Trade			4.83%
	Ave Losing Trade			-3.47%
	Number of Trades			31
	Percent Long			47%

Primary Data Source: Bloomberg, 2015

RSI (14) Model Backtest Results: Secular Bear Market From September 1929 to April 1942

Based on the test results, the RSI (14) model outperformed buy and hold by 59.00% from September 1929 to April 1942 (Figure 15). Including transaction costs for 25 roundtrip trades (i.e., for both buy and sell), the RSI (14) model outperformed buy and hold by 38.33%. Over the 1929 to 1942 time periods, an initial investment of $1 million generated $825,795 for the RSI (14) model, $655,482 adjusted for transaction costs, and $235,572 for buy and hold.

Figure 15. The RSI(14) model output with transaction costs compared to buy and hold for the period of September 1929 to April 1942



Much like the previous two secular bear markets analyzed, the majority of outperformance generated by the RSI (14) model from September 1929 to April 1942 was due to the prevention of losses. The RSI (14) model worked well at preventing losses during the following years compared with buy-and-hold: 1929–1931, 1937, and 1940–1942. The maximum drawdown for the RSI (14) model was -35.71% (1931) compared with -47.07% (1931) for buy and hold (Table 11).

Evidence of increased downside risk protection is provided in Table 11, depicted by the standard deviation metric. For the bear market period, the RSI (14) model's average standard deviation was 6.08% lower than buy and hold.

Table 11. Performance of the strategy during the 1929–1942 time period

Secular Bear Market (9/6/1929 - 4/28/1942)					RSI(14) Model	
	Returns				Trade Data	
Year	RSI (14) Model	S&P 500 Buy-and-Hold	Relative Performance	Year	No. of Trades	Weeks/Yr Invested (%)
1/1/1942-4/28/1942	0.00%	-23.46%	23.46%	1/1/1942-4/28/1942	0	0.00%
1941	-6.18%	-17.86%	11.68%	1941	2	40.38%
1940	0.92%	-15.09%	16.01%	1940	2	38.46%
1939	-24.83%	-5.18%	-19.65%	1939	4	46.15%
1938	15.11%	24.55%	-9.44%	1938	1	73.08%
1937	-0.11%	-38.59%	38.48%	1937	1	17.31%
1936	17.44%	27.92%	-10.48%	1936	3	51.85%
1935	42.99%	41.37%	1.62%	1935	1	80.77%
1934	-3.31%	-4.71%	1.40%	1934	2	23.08%
1933	48.24%	45.97%	2.27%	1933	2	57.69%
1932	-24.58%	-14.78%	-9.80%	1932	1	55.77%
1931	-35.71%	-47.07%	11.36%	1931	4	42.31%
1930	-4.67%	-28.48%	23.81%	1930	1	11.54%
9/6/1929 to 12/31/1929	-10.00%	-32.61%	22.61%	9/6/1929 to 12/31/1929	1	7.69%
				Total	25	
Combined Yearly Returns (%)				Trades	No. of Trades	Wks/Yr Invested (%)
Average	1.09%	-6.29%	7.38%	Average	1.8	39.15%
Median	-1.71%	-14.94%	6.82%	Median	1.5	41.34%
Max	48.24%	45.97%	38.48%	Max	4.0	80.77%
Min	-35.71%	-47.07%	-19.65%	Min	0.0	0.00%
St. Dev	23.75%	29.87%	16.55%			
Batting Average	35.71%	28.57%	71.43%			
Overall Performance	-17.40%	-76.40%	59.00%			

Primary data source: Bloomberg, 2014

The RSI (14) model generated 25 sets of buy/sell trades for the September 1929 to April 1942 time period. The model's batting average for success against buy and hold was 41.94%, with an average trade return at 0.46% compared to buy and hold at -2.61%. Standard deviation for the model was lower at 18.55%, compared to 27.44% for buy and hold. Maximum drawdown from the trades was better for the model at -24.58% compared to buy and hold at -37.65%. The model was long 39% of the time during the 1929–1942 time period (Table 12).

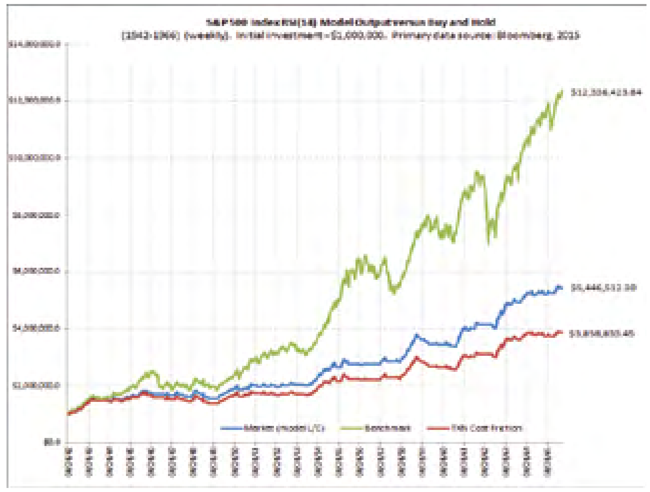
Table 12. Trading activity for the strategy during the 1929–1942 time period

Buy Trades (Long)	Sell Trades (Cash)	RSI(14) Model Performance	Buy & Hold Performance	Relative Performance
09/06/29	10/04/29	-10.00%	-21.93%	11.93%
03/28/30	05/09/30	-4.67%	-34.85%	30.18%
01/30/31	04/24/31	-5.56%	-5.74%	0.18%
07/03/31	08/07/31	-10.81%	-8.32%	-2.49%
08/28/31	09/11/31	-9.29%	-23.37%	14.08%
11/13/31	12/04/31	-15.86%	-22.20%	6.34%
02/26/32	04/08/32	-24.58%	-37.65%	13.07%
07/22/32	02/24/33	13.46%	43.08%	-29.62%
04/21/33	09/29/33	30.65%	48.12%	-17.47%
01/26/34	03/16/34	-1.81%	-16.70%	14.89%
11/16/34	12/21/34	-1.53%	3.59%	-5.12%
01/04/35	02/08/35	-5.05%	-5.89%	0.84%
04/12/35	04/03/36	70.61%	74.97%	-4.36%
07/17/36	08/28/36	1.66%	7.73%	-6.07%
10/09/36	12/11/36	1.60%	5.16%	-3.56%
01/15/37	03/19/37	-0.11%	-37.26%	37.15%
03/04/38	03/18/38	-8.45%	-6.11%	-2.34%
04/22/38	02/03/39	17.70%	25.36%	-7.66%
03/10/39	03/24/39	-7.86%	-7.71%	-0.15%
07/21/39	08/25/39	-8.27%	8.11%	-16.38%
09/15/39	12/08/39	-5.43%	-7.19%	1.76%
01/12/40	01/26/40	0.16%	-13.44%	13.60%
08/30/40	01/31/41	-4.10%	-7.05%	2.95%
06/20/41	10/17/41	-1.43%	-23.46%	22.03%
04/28/42				
	Average	0.46%	-2.61%	1.24%
	Median	-4.39%	-7.12%	0.45%
	MAX	70.61%	74.97%	15.33%
	MIN	-24.58%	-37.65%	-7.46%
	St Dev	18.55%	27.44%	5.44%
	Batting Ave	28.00%	32.00%	41.94%
	Ave Winning Trade			13.00%
	Ave Losing Trade			-8.66%
	Number of Trades			25
	Percent Long			39%
Primary Data Source: Bloomberg, 2015				

RSI (14) Model Backtest Results: Secular Bull Market From May 1942 To January 1966

Based on the test results, the RSI (14) model underperformed buy and hold by 600.63% from May 1942 to January 1966. Including transaction costs for 54 round trip trades (i.e., one buy and one sell), the RSI (14) model underperformed buy and hold by 629.78%. Over the 1942 to 1966 time period, an initial investment of $1 million generated $5,446,512 for the RSI (14) model, $3,858,833 adjusted for transaction costs, and $12,336,423 for buy and hold (Figure 16).

Figure 16. The RSI(14) model output with transaction costs compared to buy and hold for the period of May 1942 to January 1966



Relevant examples of the RSI (14) model's underperformance to buy and hold during the April 1942 to January 1966 time period can be seen in the combined yearly returns statistics in Table 13. The average yearly return for the model was 3.6% less than buy and hold. The best performing year for the model was 39.31% compared to buy and hold, which was 45.02%. The model did provide additional risk protection in down markets with its maximum drawdown value at -9.39% compared to -14.31% for buy and hold. The standard deviation for the model was lower than buy and hold by 3.57% (Table 13).

Table 13. Performance of the strategy during the 1942–1966 time period

Secular Bull Market (4/28/1942 - 1/14/1966)	Returns				RSI(14) Model Trade Data	
Year	RSI (14) Model	S&P 500 Buy & Hold	Relative Performance	Year	No. of Trades	Weeks/Yr Invested (%)
12/31/1965 - 1/14/1966	0.00%	1.18%	-1.18%	12/31/1965 - 1/14/1966	0	0.00%
1965	8.01%	9.06%	-1.05%	1965	4	59.62%
1964	2.39%	12.97%	-10.58%	1964	1	67.31%
1963	8.17%	18.89%	-10.72%	1963	1	73.08%
1962	2.18%	-11.81%	13.99%	1962	2	76.92%
1961	15.23%	23.13%	-7.90%	1961	2	78.85%
1960	-8.99%	-2.97%	-6.02%	1960	3	30.77%
1959	5.96%	8.48%	-2.52%	1959	4	53.85%
1958	32.37%	38.06%	-5.69%	1958	1	93.68%
1957	4.04%	-14.31%	18.35%	1957	1	42.31%
1956	-4.97%	2.62%	-7.59%	1956	2	17.31%
1955	8.45%	26.40%	-17.55%	1955	2	67.31%
1954	39.31%	45.02%	-5.71%	1954	1	94.23%
1953	-8.87%	-6.62%	-2.25%	1953	4	40.38%
1952	0.91%	11.78%	-10.87%	1952	4	48.08%
1951	4.21%	16.35%	-12.14%	1951	3	42.31%
1950	5.14%	21.68%	-16.54%	1950	2	71.15%
1949	12.64%	10.46%	2.18%	1949	2	51.92%
1948	4.19%	0.65%	3.54%	1948	1	28.85%
1947	6.64%	0.00%	6.64%	1947	4	80.77%
1946	-9.39%	-11.87%	2.48%	1946	4	28.85%
1945	17.98%	30.23%	-12.25%	1945	3	69.23%
1944	7.90%	13.80%	-5.90%	1944	4	32.69%
1943	19.01%	19.45%	-0.41%	1943	0	59.89%
5/29/1942 - 12/31/1942	19.88%	19.88%	0.00%	5/29/1942 - 12/31/1942	1	100.00%
				Total	54	
Combined Yearly Returns (%)				Trades		Wks/Yr Invested (%)
Average	7.70%	11.30%	-3.60%	Average	2.16	56.37%
Median	5.96%	11.78%	-5.69%	Median	2	59.62%
Max	39.31%	45.02%	18.35%	Max	4	100.00%
Min	-9.39%	-14.31%	-17.55%	Min	0	0.00%
St. Dev	11.71%	15.28%	8.62%			
Batting Average	80.00%	76.00%	24.00%			
Overall Performance	222.80%	1363.67%	-1141.67%			

Primary data source: Bloomberg, 2015

The RSI (14) model generated 54 sets of buy/sell trades for the May 1942 to January 1966 time period. The model's batting average for success against buy and hold was 22.64%, with an average trade return at 3.73% compared to buy and hold at 5.71%. Standard deviation for the model based on trading data was modestly lower at 10.31% compared to 12.87% for buy and hold. Maximum drawdown from the trades for the model was at -7.12% compared to buy and hold at -19.29%, while the maximum return for the model was 42.70% compared to 51.04% for buy and hold. The model was long 56% of the time during the 1942–1966 time period (Table 14).

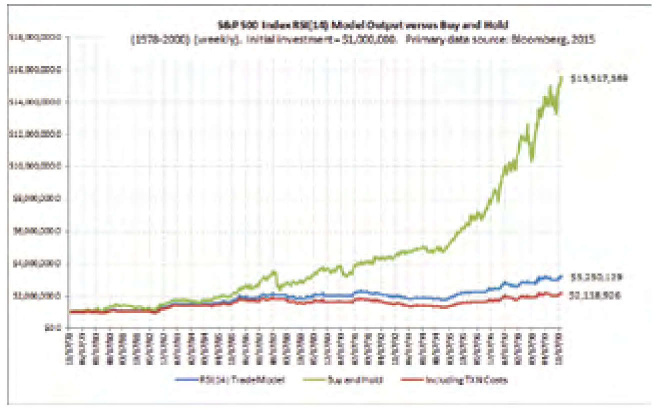
Table 14. Trading activity for the strategy during the 1942–1966 time period

Buy Trades (Long)	Sell Trades (Cash)	RSI(14) Model Performance	Buy & Hold Performance	Relative Performance
05/29/42	08/06/43	42.70%	51.04%	-8.34%
03/17/44	04/07/44	-2.19%	-2.52%	0.33%
05/12/44	07/14/44	10.25%	8.50%	-0.83%
10/13/44	11/03/44	-1.00%	1.92%	-2.92%
12/15/44	03/16/45	6.18%	10.78%	-4.60%
04/27/45	07/06/45	1.43%	7.01%	-5.58%
09/07/45	12/28/45	10.04%	16.34%	-6.30%
01/18/46	03/01/46	-5.96%	3.28%	-9.24%
04/19/46	05/24/46	-0.53%	-0.32%	-0.21%
06/07/46	06/21/46	-3.13%	-19.29%	16.16%
12/27/46	03/14/47	-2.70%	-0.20%	-2.50%
05/23/47	09/12/47	5.50%	7.00%	-1.90%
10/10/47	11/21/47	0.26%	-2.03%	2.29%
11/28/47	12/05/47	2.34%	0.93%	1.41%
12/26/47	01/23/48	-5.09%	0.20%	-5.29%
04/02/48	06/25/48	11.09%	0.18%	1.91%
01/14/49	02/04/49	-0.98%	-3.15%	2.17%
07/15/49	06/30/50	19.65%	31.70%	-1.02%
09/22/50	12/08/50	-0.21%	7.36%	-7.57%
01/05/51	03/23/51	4.12%	9.20%	-4.90%
08/10/51	10/26/51	0.09%	4.96%	-4.87%
01/04/52	02/22/52	-3.18%	0.42%	-3.60%
04/04/52	04/25/52	-2.00%	1.46%	-3.46%
06/13/52	08/29/52	2.71%	5.29%	-2.58%
11/20/52	02/13/53	0.31%	2.03%	-1.72%
03/20/53	04/03/53	-3.63%	-5.35%	1.72%
08/07/53	08/28/53	-4.20%	-1.74%	-2.46%
10/23/53	10/22/54	31.95%	37.37%	-7.80%
11/19/54	08/19/55	25.62%	38.41%	5.08%
09/23/55	10/07/55	-7.12%	7.01%	-14.13%
03/23/56	04/20/56	-2.19%	1.06%	-3.25%
07/20/56	08/24/56	-2.84%	-7.98%	5.14%
03/15/57	08/16/57	4.04%	-5.31%	9.07%
01/24/58	02/13/59	30.40%	35.20%	-3.58%
03/20/59	07/31/59	7.31%	6.17%	-2.69%
08/07/59	08/21/59	-1.32%	-1.45%	0.13%
12/25/59	01/22/60	-2.75%	-1.75%	-1.00%
06/10/60	07/22/60	-5.61%	-1.66%	-3.95%
08/19/60	09/16/60	-3.33%	-2.09%	-1.24%
11/18/60	06/23/61	16.73%	21.78%	-5.05%
08/04/61	09/22/61	-1.85%	0.53%	-2.38%
10/27/61	12/29/61	4.70%	-13.49%	18.19%
08/31/62	09/28/62	-4.82%	-0.58%	-4.24%
11/09/62	07/19/63	16.20%	21.62%	-5.34%
08/16/63	10/04/63	1.90%	3.27%	-1.37%
11/01/63	11/15/63	-2.00%	3.26%	-5.26%
01/10/64	06/05/64	3.65%	9.34%	-5.69%
07/10/64	08/14/64	-1.21%	1.20%	-2.41%
10/02/64	12/04/64	-0.01%	2.82%	-2.83%
01/22/65	02/19/65	-0.01%	0.07%	-0.08%
03/05/65	03/19/65	0.05%	2.40%	-2.35%
04/23/65	05/28/65	-0.52%	0.27%	-0.79%
07/23/65	12/10/65	9.19%	11.22%	-1.90%
01/14/66				
	Average	3.73%	5.71%	-1.78%
	Median	-0.01%	1.92%	-2.46%
	MAX	42.70%	51.04%	18.19%
	MIN	-7.12%	-19.29%	-14.13%
	St Dev	10.31%	12.87%	5.36%
	Batting Ave	49.06%	69.81%	22.64%
	Ave Winning Trade			4.89%
	Ave Losing Trade			-3.76%
	Number of Trades			54
	Percent Long			56%
Primary Data Source: Bloomberg, 2015				

RSI (14) Model Backtest Results: Secular Bull Market From November 1978 to January 2000

Based on the test results, the RSI (14) model underperformed buy and hold by 1141.67% from November 1978 to January 2000 (Figure 17). Including transaction costs for 56 roundtrip trades (i.e., one buy and one sell), the RSI (14) model underperformed buy and hold by 1176.07%. Over the 1978 to 2000 time period, an initial investment of $1 million generated $3,230,129 for the RSI (14) model, $2,118,926 adjusted for transaction costs, and $15,517,369 for buy and hold.

Figure 17. The RSI(14) model output with transaction costs compared to buy and hold for the period of November 1978 to January 2000



Relevant examples of the RSI (14) model's underperformance to buy and hold during the November 1978 to January 2000 time period can be seen in the combined yearly returns statistics in Table 15. The average yearly return for the model was 7.5% less than buy and hold. The best performing year for the model was 30.44% compared to buy and hold, which was 34.11%. The model did provide additional risk protection in down markets with its maximum drawdown value at -5.62% compared to -9.73% for buy and hold. The standard deviation for the model was lower than buy and hold by 3.03% (Table 15).

Table 15. Performance of the strategy during the 1978–2000 time period

Secular Bull Market (11/17/1978 - 1/14/2000)					RSI(14) Model	
	Returns				Trade Data	
Year	RSI (14) Model	S&P 500 Buy & Hold	Relative Performance	Year	No. of Trades	Weeks/Yr Invested (%)
11/17/1978-12/29/1978	0.00%	1.79%	-1.79%	11/17/1978-12/29/1978	0	0.00%
1979	-4.83%	12.31%	-17.12%	1979	3	63.46%
1980	7.33%	25.89%	-18.56%	1980	2	75.00%
1981	-2.95%	-9.73%	6.78%	1981	1	7.69%
1982	-3.57%	14.76%	-18.33%	1982	4	51.85%
1983	20.10%	17.27%	2.83%	1983	1	55.77%
1984	0.09%	6.81%	-0.72%	1984	2	30.77%
1985	19.64%	26.33%	-6.69%	1985	2	75.00%
1986	5.44%	14.62%	-9.18%	1986	3	46.15%
1987	10.58%	2.08%	8.50%	1987	3	48.08%
1988	-2.55%	12.40%	-14.95%	1988	4	46.15%
1989	15.55%	27.25%	-11.70%	1989	2	69.23%
1990	-5.62%	-6.56%	0.94%	1990	2	28.85%
1991	5.58%	26.88%	-21.30%	1991	3	67.31%
1992	-4.17%	4.46%	-8.63%	1992	5	55.77%
1993	2.23%	7.06%	-4.83%	1993	5	59.62%
1994	0.74%	-1.54%	2.28%	1994	2	32.69%
1995	30.44%	34.11%	-3.67%	1995	2	88.46%
1996	4.63%	20.26%	-15.63%	1996	2	36.54%
1997	10.97%	31.01%	-20.04%	1997	3	46.15%
1998	16.55%	19.53%	-2.98%	1998	2	50.00%
1999	3.03%	19.53%	-16.50%	1999	3	61.54%
1/1/2000 - 1/14/2000	-0.28%	-0.28%	0.00%	1/1/2000 - 1/14/2000	0	0.00%
				Total	56	
Combined Yearly Returns (%)				Trades		Wks/Yr Invested (%)
Average	5.60%	13.05%	-7.45%	Average	2.4	47.78%
Median	3.03%	14.62%	-6.69%	Median	2	50.00%
Max	30.44%	34.11%	8.50%	Max	5	88.46%
Min	-5.62%	-9.73%	-21.30%	Min	0	0.00%
St. Dev	9.51%	12.54%	9.08%			
Batting Average	65.22%	82.61%	21.74%			
Overall Performance	222.00%	1363.67%	-1141.67%			

Primary data source: Bloomberg, 2015

The RSI (14) model generated 56 sets of buy/sell trades for the November 1978 to January 2000 time period. The model's batting average for success against buy and hold was 18.87%, with an average trade return at 2.27% compared to buy and hold at 5.19%. Standard deviation for the model based on the trade data was modestly lower at 9.15% compared to 9.80% for buy and hold. The model was long 47% of the time during the 1978–2000 time period (Table 16).

Table 16. Trading activity for the strategy during the 1978–2000 time period

Buy Trades (Long)	Sell Trades (Cash)	RSI(14) Model Performance	Buy & Hold Performance	Relative Performance
01/12/79	02/16/79	-1.26%	0.76%	-2.02%
03/16/79	05/11/79	-2.16%	1.39%	-3.55%
09/15/79	10/19/79	-0.40%	6.77%	-7.17%
12/14/79	03/14/80	-3.20%	2.13%	-5.33%
05/30/80	11/07/80	16.13%	25.05%	-8.92%
11/21/80	12/12/80	-7.10%	-9.24%	2.14%
12/04/81	01/01/82	-2.94%	-7.95%	5.01%
04/09/82	06/04/82	-5.27%	-4.35%	-0.92%
07/23/82	09/06/82	-18.59%	5.34%	-23.93%
08/27/82	07/22/83	44.21%	41.25%	2.96%
08/10/84	11/23/84	0.91%	-1.11%	2.02%
11/30/84	12/07/84	-0.81%	1.64%	-2.45%
12/28/84	01/11/85	0.99%	3.04%	-2.05%
01/18/85	08/16/85	8.63%	13.07%	-4.44%
11/08/85	04/11/86	21.81%	26.82%	-5.01%
06/06/86	07/18/86	-3.79%	2.24%	-6.03%
12/05/86	01/02/87	-1.88%	6.02%	-7.90%
01/16/87	04/24/87	5.72%	15.28%	-9.56%
06/19/87	07/31/87	4.89%	5.22%	-0.33%
08/07/87	09/11/87	-0.32%	-17.98%	17.66%
03/11/88	04/22/88	-1.81%	2.39%	-4.20%
06/10/88	07/29/88	0.28%	-0.22%	0.50%
09/16/88	11/18/88	-1.54%	2.08%	-3.62%
12/16/88	03/31/89	6.72%	9.07%	-2.35%
04/14/89	07/07/89	7.81%	14.12%	-6.31%
08/04/89	10/20/89	0.94%	3.12%	-2.18%
05/18/90	08/03/90	-9.05%	-7.58%	-1.47%
12/07/90	01/11/91	-3.82%	2.54%	-6.36%
01/25/91	06/28/91	10.44%	13.35%	-2.91%
07/26/91	09/20/91	1.83%	0.86%	0.97%
10/25/91	11/22/91	-2.10%	9.15%	-11.25%
01/03/92	03/13/92	-3.22%	-2.46%	-0.76%
04/24/92	06/12/92	0.18%	0.63%	-0.45%
07/24/92	08/28/92	-0.27%	2.75%	-3.02%
09/18/92	10/02/92	-2.95%	0.88%	-3.83%
11/20/92	01/15/93	2.46%	4.20%	-1.74%
02/12/93	02/26/93	-0.27%	1.18%	-1.45%
03/12/93	04/09/93	-1.78%	-2.85%	1.07%
04/23/93	06/23/93	1.41%	4.38%	-2.97%
08/20/93	11/12/93	2.02%	2.46%	-0.44%
12/24/93	02/11/94	0.60%	-1.86%	2.46%
06/10/94	07/01/94	-2.72%	-0.34%	-2.38%
08/05/94	09/30/94	1.23%	1.68%	-0.45%
01/20/95	11/03/95	27.06%	29.09%	-2.03%
11/24/95	01/19/96	1.98%	9.40%	-7.42%
02/09/96	03/08/96	-3.48%	4.54%	-8.02%
09/27/96	12/20/96	9.13%	12.29%	-3.16%
01/24/97	03/21/97	1.76%	7.04%	-5.28%
05/09/97	08/22/97	11.98%	7.04%	4.94%
10/10/97	10/24/97	-2.62%	5.49%	-8.11%
02/13/98	06/05/98	9.19%	12.38%	-3.19%
07/03/98	07/31/98	-2.25%	-1.81%	-0.44%
11/13/98	02/19/99	10.08%	15.00%	-4.92%
03/12/99	06/04/99	2.56%	8.40%	-5.84%
07/09/99	07/30/99	-5.31%	2.72%	-8.03%
11/12/99	01/14/00	4.05%	4.05%	0.00%
	Average	2.27%	5.19%	-2.84%
	Median	0.23%	2.75%	-2.45%
	MAX	44.21%	41.25%	17.66%
	MIN	-18.59%	-17.98%	-23.93%
	St Dev	9.15%	9.80%	5.40%
	Batting Ave	51.79%	77.36%	18.87%
	Ave Winning Trade			3.97%
	Ave Losing Trade			-4.30%
	Number of Trades			56
	Percent Long			47%
Primary Data Source: Bloomberg, 2015				

Discussion

The RSI (14) model backtest results presented herein suggest that employing a trend-trading strategy to mitigate downside risk comes at a cost. The model's relative performance results versus buy and hold in a secular bear market compared to a secular bull market were significantly different.

For the three secular bear markets analyzed, the annual performance results generated by the model were compelling compared to buy and hold. The model's yearly percent returns and standard deviation were, on average, better than buy and hold, meaning the model achieved higher relative returns with lower risk. For the three markets analyzed, the model had outperformed buy and hold, on average, by 39.2%, mainly due to moving the portfolio to cash during turbulent and volatile bear market periods, which reduced the negative effects associated with large drawdowns. For each secular bear market analyzed, the backtest results identified that the model outperformed buy and hold after factoring in the frictional costs associated with trading/transactions. The average transaction cost per roundtrip trade (i.e., a buy and a sell) for the three secular bear markets was 0.49%.

For the two secular bull markets analyzed, the annual performance results generated by the model were not compelling compared to buy and hold. Even though the model's standard deviation on average was lower, it significantly underperformed buy and hold, meaning the model achieved lower relative returns with lower risk. For the two markets analyzed, the model had underperformed buy and hold, on average, by 871.15%, mainly due to moving the portfolio to cash in a bullish trending market. For each secular bull market analyzed, the backtest results identified the frictional costs associated with trading/transactions that negatively impacted the performance of the model. The average transaction cost per roundtrip trade for the two secular bull markets was 0.54%.

The model's percent of time invested in the market significantly impacted relative performance depending on whether or not a secular bear or bull trend was in effect. For the three secular bear markets analyzed, the backtest identified that the model was invested in the market, on average, 44% of the time. On balance, the net result of not being fully invested in a bear market helped the model outperform buy and hold. For the two secular bull markets analyzed, the backtest identified that the model was invested in the market, on average, 51.5% of the time. On balance, the net result of not being fully invested in a bull market created a headwind for the model that significantly underperformed buy and hold. Transaction costs were also an additional headwind for the model to outperform buy and hold in a secular bull market.

The direction of the underlying secular trend is an important factor to understand and directly impacts the success of the model compared to buy and hold. In a secular bear market, the cyclical bear markets tend to be more damaging, and the cyclical bull markets tend to be less impactful. In this scenario, there becomes an increased need to employ a trend-trading strategy to outperform buy and hold. In a secular bull market, the cyclical bear markets tend to be less damaging, and the cyclical bull markets more impactful. In this scenario more reliance on buy and hold increases the likelihood of outperforming a mechanical trend-trading strategy.

Further study is recommended to include additional technical indicators to the backtest, such as a price moving average to help better diagnose the underlying secular trend as an input to the model. Providing an additional trend diagnosing factor may increase the level of confirmation of the RSI (14) model-generated trade signals.

Conclusion

The intent of this research paper is to present a simple trend-trading model that will manage risk in investing. Using the RSI (14) weekly trend-trading model, investors are able to increase their returns within a secular bear market by avoiding many of the primary or cyclical bear trending markets.

The RSI (14) model reduces the risk of the investment by eliminating the fat tails or extreme values associated with good and bad events. During a secular bear market, the risk based on standard deviation is less, and the overall returns are higher.

In a secular bear market, trade frequency of two or less (buy and sell = 1) per year resulted in higher relative returns than buy and hold, and trade frequency of three or more per year resulted in lower relative returns. The model's best scenario was two trades per year, which occurred 10 times out of 34 years (29%). For this case, the model was invested in the market, on average, 41.89% of the time, generating an average relative excess return of 12.67% compared with buy and hold.

The RSI (14) trend-trading model results underperformed the buy and hold strategy during a secular bull trending market. For the cases presented, the model did in fact generate lower standard deviation than buy and hold. However, due to the fact that the model was not 100% invested, and accounting for the frictional aspects of trading/transaction costs, buy and hold overall performance was much better in a secular bull market compared to the model.

In a secular bull market, trade frequency of one or less (buy and sell = 1) per year resulted in modestly higher relative returns for the model compared to buy and hold, and trade frequency of two or more per year resulted in lower relative returns for the model. The model's best scenario was one trade per year, which occurred 9 times out of 46 years (19.6%). For this case, the model was invested in the market, on average, 51.54% of the time, generating an average relative excess return of 1.63% compared with buy and hold.

In conclusion, wrestling with a grizzly bear (or bear market) is never going to be an easy task; however, the overall backtest results presented herein suggest that employing a more tactical RSI (14) trend-trading strategy during a secular bear market increases the likelihood of outperforming the U.S. equities benchmark compared with buy and hold.

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Software and Data

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StockCharts Technical Ranking (SCTR) System: How the SCTR Indicator Can Help Novice and Advanced Investors Rapidly Evaluate a Stock in Real Time

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Abstract

This paper defines the StockCharts Technical Ranking (SCTR)© indicator. The indicator has four main features. It ranks how a stock price action is performing to a large peer group in real time, assigning a value between 0–100. SCTR plots the history of the stock's relative performance, including current value. The value does not change across different plotted time frames of hourly, daily or monthly. The SCTR provides a single value for a stock performance compared to its peers for use by technical or fundamental investing styles.

Introduction

This paper defines how I use the StockCharts.com Technical Ranking (SCTR)© indicator. This paper is also the first introduction of the SCTR to the global professional community of technical analysis. The indicator has been presented in workshops designed to help users of the StockCharts.com website over the years. It was recently refined in 2014. This documents one of the many interpretations and uses for the data of the plotted indicator to demonstrate the relative value.

The four features of the SCTR

The indicator has four main features. The SCTR ranks how a stock price action is performing relative to a defined peer group in real time. This is a larger group than just an industry group. StockCharts.com has created three groups based on Market Cap in large markets like the U.S. market. The SCTR gives a value between 0–100. A ranking of 94 would suggest the stock is behaving better than 94% of the stocks in the peer group.

Secondly, when plotted as an indicator, it also shows the history of the stock's relative performance to its group. The value of the SCTR indicator at a point in time is the same across all timeframes of minute, 10-minute, hourly, daily or monthly.

The SCTR indicator has the ability to quickly outline a stock's performance compared to its peers in one number for use by technical or fundamental investing styles. It can educate new or experienced investors by calculating a value for the relative quality of price movement even though they all have a different price. The SCTR quickly disseminates which stocks have better price action than others. Once the indicator is explained, investors can quickly evaluate a stock's relative price action compared to other stocks in the group in a tabular or chart format. Apple currently has an SCTR of 31.5, and this paper will supply information on understanding that value.

The last benefit of the SCTR is that it helps investors eventually get a portfolio of very fast-moving stocks and provides a simple exit plan to retain the gains. When you are in very strong SCTR stocks and each one is trending very quickly, your portfolio can capture dynamic, outsized gains, and the indicator leads you to these stocks every day.

Materials and Methods

Calculating an SCTR

Each individual stock or ETF is calculated against six different measurements and given a value. (Table 1)

Table 1. SCTR Calculation Parameters

SCTR Calculation	
Long-Term Indicators (Weighting)	
Percent above/below the 200-Day EMA	30%
125-Day Rate Of Change (ROC)	30%
Medium-Term Indicators (Weighting)	
Percent above/below 50 EMA	15%
20-Day Rate Of Change (ROC)	15%
Short-Term Indicators (Weighting)	
3-Day slope of PPO Histogram	5%
14-Day RSI	5%

The resulting value is compared to a peer group and creates a ranking of the strongest price action to the weakest price action. One important component is that stocks are ranked compared to a peer group that has a controlled size. StockCharts.com currently uses Large Cap, Mid Cap, Small Cap, and ETFs to create peer comparisons for U.S. equities and ETFs due to the large size of the U.S. market. Using Canada as an example, all of the stocks and ETFs in the market are used as one peer group. As the SCTR is not market-cap-weighted, this differs substantially from comparing to the S&P 500 in Relative Strength.

Historical Data. The historical data has been built up over an eight-year period from 2007–2015. Because you need all the stocks at the same time to rank each stock against one another, it is very difficult to go back and replicate the data. Using the historical database, we have now developed a much greater understanding of the data and how the SCTR behaves in bull markets. The bear market of 2007–2009 gave us some information for declining markets. However, we have two years of bear market data and six years of bull market data. The SCTR has excellent data from fall 2007 forward. With this methodology, we are able to create a ranking of stocks improving or falling out of favor continuously.

Displaying the Data. Table 2 shows the SCTR being used to sort stocks within an industry group.

By ranking the Equities and ETFs based on one value within their peer group, the SCTR calculation makes the stock's

Table 2. Table Form of the SCTR Ranking

Sector Summary: Toys

View performance data using Intraday *Members: Log in to see performance updates on an intraday basis.*
Hide stocks under $1

31 Jul 2015, 4:00 PM

Tracking Symbol	Name	SCTR	Close	Chg	% Chg
HAS	Hasbro, Inc.	98.7	78.74	-1.25	-1.56
EA	Electronic Arts, Inc.	97.7	71.55	-0.75	-1.04
JAKK	JAKKS Pacific, Inc.	94.1	9.85	0.02	0.20
GLUU	Glu Mobile Inc.	88.3	5.87	-0.05	-0.85
KING	King Digital Entertainment Plc	81.3	15.53	0.06	0.39
TTWO	Take-Two Interactive Software, Inc.	78.6	31.58	-0.23	-0.72
ZNGA	Zynga Inc.	22.9	2.48	0.01	0.40
MAT	Mattel, Inc.	8.9	23.21	-0.23	-0.98

Figure 1. SCTR Plotted as an Indicator With an 18-Month Hasbro

relative behavior much easier to evaluate when presented in table form.

Plotting the Indicator. With the SCTR, each stock is ranked on the basis of the price performance of the six variables mentioned above, and a final total is calculated. Those stocks with exceptional traits rise to the top and can burst or stay there for months at a time. Using the indicator in plotted form, the SCTR demonstrates who is continuously performing better than their peers.

Figure 1 demonstrates the Hasbro Toy Company stock price with the SCTR and the S&P 500 Relative Strength.

As this indicator is new to the technical analysis community, I will only demonstrate one of the many interpretations for the indicator rather than try to briefly demonstrate many of the possibilities.

Defining a Trade Trigger on the SCTR

I define a single parameter using 75% on the SCTR as a minimum threshold for owning the stock. Two conditions exist.

Buy on the open the day after a buy signal is generated moving above 75%.

Sell on the open the day after a sell signal is generated moving below 75%. (Figure 2)

Figure 2. Hasbro With the SCTR and a Red Line Marking 75%

Figure 3. SCTR Plotted as an Indicator on Hasbro, Inc.

Crossing above the red line at 75% represents a buy signal to own the stock. This directs the investor to the better performing equities exhibiting a stronger price move within an industry group, a sector or overall leadership at any given time. By manipulating the sort criteria you can identify top equities overall, top within a sector, or top within an industry group.

Defining the Output From Individual Trade Data

Tables 2–8 showcase the results of analyzing four stocks and their trading performance over the 8-year history using the simple rule of owning it above 75. I have broken the analysis into five line items.

1. The "Bear Market" results are broken out for the Great Financial Crisis of 2007 to 2009. Can the SCTR help navigate bear markets?
2. The "Bull Market" period is from March 09, 2015, to October 09, 2015.
3. The "Both Markets" entry evaluates the combined results of the bear and bull markets.
4. Evaluate the size of the gains from sustained high-level periods, titled "Runs Longer Than 5 Days".
5. The final study, titled "Waiting For A Weekly Entry" evaluates the long entries after five continuous days above SCTR=75. Taking the periods established in the sustained periods, we looked to see how much damage would occur by waiting a week to enter rather than entering on the next morning. This is designed to eliminate some of the whipsaws that occur with such a strict criteria and help less nimble investors like portfolio managers. To clarify, this should demonstrate the results of those long periods based on an entry on the 6th day. Being slower to execute the trade affects profitability shown on the "Entry Difference" line, which is the change in profitable trades by waiting a week rather than entering on the first signal.

Results

Hasbro Inc.

Staying with Hasbro, Inc., we can see the stock currently has a high SCTR. I have used Hasbro, Inc. in the example above, as it was on the top of the industry group. The top white area beside Hasbro shows the total number of days since the start of the first trade, the original price in 2007, and the current price in 2015. The Range Maximum is the dollar value between the 8-year low and the high. (Figure 3)

Table 2. Results of Hasbro, Inc. (HAS) When SCTR Is Greater Than 75

Hasbro	# Days			Price in 2007	Price in 2015	Range Maximum
Hasbro	1,977			$21.73	$74.44	$66.80
	# Days	Total Days	% of Time in Market	# of Trades	Percent Profitable	Cumulative Gain
Bear Market	202	320	63%	13	62%	$3.87
Bull Market	442	1657	27%	33	45%	$21.55
Both Markets	644	1977	33%	46	50%	$25.42
Runs Longer Than 5 Days	566			10	80%	$29.86
Waiting for a Weekly Entry	526			10	60%	$22.95
Entry Difference					-20%	-23%

The Average Gain for Hasbro depending on the primary trend is shown in Table 3.

Table 3. Results of Hasbro, Inc. (HAS) Average Gain/Trade

Hasbro	Bear Market	Bull Market
Average Loss	$(0.52)	$(0.65)
Average Gain	$0.88	$2.22

Apple, Inc.

Apple is a well-known name of which most technicians can visualize the chart pattern almost intuitively. By choosing Apple to test the SCTR trading system, this may enable a stronger understanding between the stock knowledge and the SCTR behavior. The stock suffered major downtrends in 2008, 2012 and 2015. Once again, we only want to own the stock when it is above the SCTR 75 level. (Figure 4)

Figure 4. SCTR Plotted as an Indicator on Apple, Inc.

The figure represents corrected data from the stock split in 2014. I used uncorrected data to analyze the indicator. Multiple periods of large corrections are visible, and we want to use the SCTR to avoid owning the stock during these corrections.

Table 4 shows the profits achieved moving in and out in both types of markets at $473.76. Investors that "Waited for a Weekly Entry" would have made $512.96, as Apple trended very well. This would have eliminated a large number of whipsaws. For the past eight years, this investor would have owned Apple 50% of the time, but missing the periods with the dramatic pullbacks.

Table 4. Results of Apple, Inc. (AAPL) When SCTR Is Greater Than 75

APPLE	# Days			Price in 2007	Price in 2015	Range Maximum
Apple	1,982			$166.10	$112.12	$860.51
	# Days	Total Days	% of Time in Market	# of Trades	Percent Profitable	Gain
Bear Market	108	325	33%	12	42%	$27.73
Bull Market	1,169	1657	71%	45	36%	$446.03
Both Markets	1,277	1982	64%	57	37%	$473.76
Runs Longer Than 5 Days	1,081		55%	22	82%	$649.91
Waiting for a Weekly Entry	997		50%	22	68%	$512.96
Entry Difference					-14%	-21%

Table 5 shows the average gain and loss for Apple. The maximum loss in the 2008 bear market was $6.93 per share, and Apple traded over $200 per share in 2007. There were two losses of $50.05 and $37.99 for Apple when the stock was over $500.

Table 5. Results of Apple Inc. (AAPL) Average Gain/Trade

Apple			
Bear Market	Bear Market	Bull Market	After Stock Split
Average Loss	$(3.75)	$(9.35)	$(2.67)
Average Gain	$10.79	$34.87	$10.90

Because of the extreme price difference after the split, I calculated the after stock split change. It was not reflective of the 7:1 share split.

Amazon

Next, we will look at Amazon, which has more seasonality. This stock is more difficult for investors to hold because of the wide seasonal swings. Additionally, the company does not produce many profits, so it has an alarming value for fundamental investors.

Figure 5. SCTR Plotted as an Indicator on Amazon, Inc.

As reflected in Figure 5, in the bear market, Amazon dropped over 50%. Two of the trades made money during the financial crisis, but the second trade was entered a month (February 9, 2009) before the March 9, 2009, market bottom. That trade is marked as a bear market trade, but it was held well into the bull market (July 31, 2009).

Table 6 illustrates holding Amazon about 40% of the time. According to the SCTR, it is subject to a large number of swings. By using the SCTR, the investor is able to sell near the top. Waiting for the weekly trade on this stock wiped out almost half of the gains because of the seasonal swings.

Amazon works well using the SCTR to help with exits. In a bull market, the winning trades were outperforming the losing trades by 4:1. The maximum drawdown was important with two distinct 10% moves in the last eight years. Seasonality does affect the SCTR ability to trend above 75 for a long time.

Table 6. Results of Amazon Inc. When SCTR Is Greater Than 75

Amazon	# Days			Price in 2007	Price in 2015	Range Maximum
Amazon	1983			$79.18	$539.80	$545.89
	# Days	Total Days	% of Time In Market	# of Trades	Percent Profitable	Gain
Bear Market	167	326	51%	4	50%	$24.50
Bull Market	710	1657	43%	26	54%	$238.38
Both Markets	877	1983	44%	30	53%	$262.88
Runs Longer Than 5 Days	852		43%	20	75%	$293.79
Waiting for a Weekly Entry	826		42%	20	40%	$163.47
Entry Difference					-35%	-44%

Table 7. Results of Amazon Inc. (AMZN) Average Gain/Trade

	Amazon	
	Bear Market	Bull Market
Average Loss	$(6.26)	$(5.70)
Average Gain	$18.51	$21.92

Skyworks

A small cap stock called Skyworks Solutions, Inc., by scanning on the SCTR, has been a top performer for years. With a move up of over 2000%, the SCTR ranking can point investors to strong stocks outside their field of knowledge, and the SCTR can help them exit with most of the gains.

In Figure 6, we can see that price action struggled through most of 2011 and 2012. The 2011 correction was over 60%. It is the ability to miss these major corrections in order to preserve capital in an industry group that makes the SCTR a valuable tool to an experienced or novice investor.

Figure 6. SCTR Plotted as an Indicator on Skyworks Solutions, Inc.

The table of performance for Skyworks is shown below.

In the bear market, Skyworks traded with positive gains. Investors would be in the stock in the bear market about 40% of the time, and possession accelerated up to 55% in the bull market. The stock had one 9% maximum drawdown. (Table 8)

Table 8. Results of Skyworks (SWKS) When SCTR Is Greater Than 75

Skyworks	#Days			Price in 2007	Price in 2015	Range Maximum
Skyworks	1,982			$8.70	$79.50	$109.03
	# Days	Total Days	% of Time In Market	# of Trades	Percent Profitable	Gain
Bull Market	935	1657	56%	26	58%	$92.11
Both Markets	1,063	1982	54%	38	50%	$92.90
Runs Longer Than 5 Days	1,081		55%	22	72%	$94.76
Waiting for a Weekly Entry	997		50%	22	41%	$84.73
Entry Difference					-31%	-11%

Table 9. Results of Skyworks Average Gain/Trade

Skyworks	Bear Market	Bull Market
Average Loss	$(0.23)	$(0.68)
Average Gain	$0.66	$6.64

The SCTR for the S&P 500 ETF (SPY)

For reference, as part of the results section, I have shown the SPY ETF with an SCTR ranking against other ETFs. While the $SPX has enjoyed a tremendous move down and up over the past eight years, the SCTR shows that it performs adequately but subpar to the moves investors could have achieved using the SCTR to point them to the most strength. (Figure 7)

Figure 7. SCTR Plotted as an Indicator on S&P 500 ETF (SPY)

The Results section has demonstrated the use of the indicator on different stocks from well-known major firms to unique product companies. The SPY ETF chart hovers around the 50 to 70 level on the SCTR. It never really can outperform on a long-term basis.

Discussion

Characteristics of Price Movements With High SCTR Rankings

The stocks presented here have had strong price action, which is what a high SCTR represents. Weak price action stocks don't come to the forefront. The four stocks presented compelling cases that you could use the SCTR rankings to work through the bear market if you wanted to stay invested. Seeing the SCTR plotted on long charts through bull and bear markets demonstrates how important it is to rotate in and out of major growth stocks. They can be weak for years after going on a strong run. Using the SCTR to search out new investing ideas can be an exciting catalyst for a portfolio. The SCTR works on ETFs as well. Sector rotation occurs very clearly on the changing leadership with the SCTR on ETFs. By choosing from different SCTR groups, this can also help an investor partition into large cap, small cap, or ETFs with ease.

Reviewing the charts above with Hasbro, the stock had a nice trading percentage with lots of small losses but demonstrates the ability to ride the trend once it starts working. With only 46 trades in eight years, and only 10 of those trades longer than a week, this company might not stay on your radar. If you know of a catalyst like Star Wars or Christmas, watching for the SCTR to break out can really help your timing. Once the stock starts to surge in momentum, other buyers will be drawn in as well.

Group Powerful Stocks Together. Having a list of high-momentum stocks in an industry group can be very powerful. The SCTR is one way to watch these stocks move higher or start to weaken. Keeping a list of the top 100 SCTR stocks helps to stay focused on only the best.

Watch for the End of a Big Run. Apple had given SCTR buy signals for over 70% of this bull market. The SCTR made its high around January, over six months ago, and looks to be weak. An understanding of Apple, Inc. currently having an SCTR ranking in the low 30% level is enlightening. With a strong earnings report, the company could jump back up to become a top performer, but until it does, you can wait. Much like Blackberry or Microsoft, it is hard to know when the company is going to put in its final high. Trading into and out of the stock on strength in the SCTR makes sure you don't end up being the last holder. Having a method of taking profits and not getting caught up in the story is very helpful. When Apple pulled back in 2012, the SCTR fell to a low 10% on the SCTR ranking.

One of the difficult concepts for investors to grasp is the importance of selling winners near the highs. As most of the companies find a sweet spot for a few years and make a major run, investors are usually still holding the stock long after the trend is over. In Apple's case, the run has been going on for 15 years. One day a pull back will mark the major long-term top. The SCTR helps force an exit of all or some of a position. Because Apple tends to trend and then break down, waiting for a weekly signal can help, which is different than Amazon.

While the success of capturing the majority of any price movement is a variable, many different systems used by other traders to visualize where money is flowing is a part of the answer for capturing strong trends. The SCTR graphically illustrates when the stock is finding a resurgence of interest. While we do not know how long a trend will last, the ability to graphically see the stock gaining or losing the characteristics of a top performer makes it easy to educate new investors. Teaching the simple methodology of looking for stocks in the top 25% seems to work quite well. When you find a few stocks at the same time that are trending, it can be an accelerator for your portfolio.

The SCTR Can Help Trade Seasonality

Amazon is world renowned, and recently they have started to focus a little more on the investor bottom line. This stock seems to surge annually, and the SCTR knowledge of when the outperformance is happening is the powerful point in the ownership of the stock. Seeing a change in relative strength is helpful, but seeing an actual ranking for the stock is compelling. The SCTR is a live indicator that can tell you what percentage of stocks this is currently outperforming. Although Amazon has only had 20 times where the trend has lasted more than a week, catching these on the first breakout rather than waiting a week for those trades led to 40% more profit.

The ability to be pushed out of a seasonal stock is very valuable, and sometimes the wavy price action covers up how well the stock is doing compared to all the other stocks in the market.

SCTR Can Help Find Really Big Movers

Skyworks has been an absolute darling stock. As it climbed out of the lows, it moved to the top of the SCTR rankings for months. It has recently broken down and will probably take multiple months to recover. Setting alerts for an SCTR of 50 on the stock can help make sure you do not forget to watch the stock. As it approaches the 75 level, you can already have it on your radar. Skyworks had 50% of the trades in the bull market work out profitably. Finding the next stock that is going to run a long time is hard, but if you can land a few a year it can make your year.

While this paper is an introduction to the SCTR as well as my interpretation of using the 75% level, this is only a start for the potential of the indicator. To my knowledge it is the only indicator that is constant across all timeframes to tell you how the stock is doing compared to peers displayed on your chart. The strength of this knowledge will probably become more obvious as we work through bull and bear markets.

Further Studies

I do find the SCTR to be a great entry signal. To further my work on the SCTR, a combination of other indicators might help the investor retain more profit on the exit There is a lot of information hidden in the SCTR data when used to help identify industry breakouts, and this needs more time spent on it. Using the various SCTR levels for pairs trading is also a compelling research area. Without question, there are enough ideas generated from the SCTR indicator to keep me busy for years.

Conclusion

To conclude, I think the SCTR visually demonstrates the need to be ready to cycle out of strong stocks when they start to underperform their peers. As well, the move above 75 on the SCTR might be one of the most important places to purchase strong stocks breaking out. I think the SCTR is one of the modern day compelling indicators to help technical studies. Marketing the SCTR ranking as an easy, valuable tool for the fundamental analyst to be aware of could be one of the major bridges for working with fundamental analysts. Having the SCTR ranking on every stock in the portfolio is a helpful clue for where to add and where to sell. For new technicians, I think the SCTR can help them understand the importance of a ranking system much like they would understand a professional sports ranking system for a league. The strongest teams are probably going to win more. To tell a friend how strong the stock is, this might be one of the simplest numbers to share. I find the SCTR to be powerful, and it is my primary search tool. For more examples, the home page at StockCharts.com has quick reference tables for SCTR in the centre. I am confident that technical and fundamental analysts will be able to evaluate a stock quickly in their mind by knowing if it has an SCTR of 11, or 47, or 89.

References

For more information on the SCTR ranking system and its construction, the StockCharts.com website has a complete writeup on the ChartSchool tab. Search for SCTR. Murphy, Anderson, Hill (2011).

The Significance of the 400-Day Moving Average as a Sell Signal as Compared to Other Moving Averages

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Abstract

This paper compares the efficacy and viability of four moving averages as sell signals. Using monthly equivalents (10-month moving average for the 200-day moving average and 20-month moving average for the 400-day moving average) we compiled data as to how a market performed after it closed below those monthly moving averages. We specifically recorded how far the market declined from the break of the moving average to its next low. We recorded all instances and summarized our findings with an average decline and median decline. We applied this study to eight different markets: S&P 500, Emerging Markets, Nasdaq, Nikkei Hong Kong, Commodities (CCI), Gold and Oil. The results as to which moving averages produced the best sell signals varied between markets and asset classes. However, for the entire study, the 20-month and 30-month moving average sell signals produced the best results. The 20-month moving average sell signal was best for the S&P 500 and Emerging Markets. The 10-month moving average and median sell signal (proxy for 200-day moving average) shows very little viability and efficacy in comparison to the longer period moving averages.

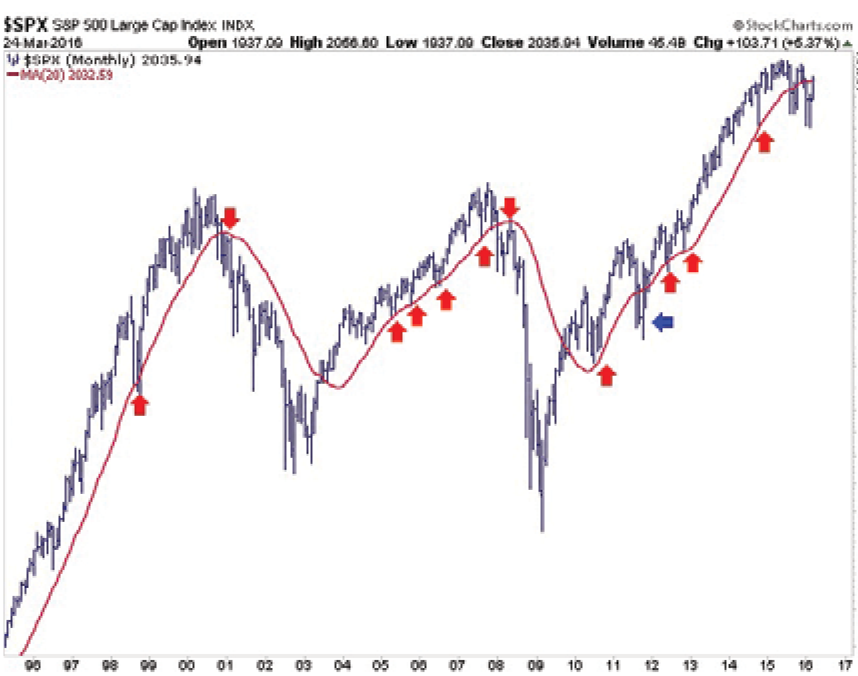
Introduction

The study of moving averages is a key component of technical analysis. Both novice and professional practitioners of technical analysis use a variety of and combination of moving averages in their trading and investing. Advanced practitioners will often use a combination of exponential (recent data weighted more heavily) moving averages and simple (all data weighted equally) moving averages. Basic moving average analysis starts with the simple 50- and 200-day moving averages.

Conventional wisdom is that the 200-day moving average is the most important moving average. It is a huge focus of basic moving average analysis and is always discussed publicly when the stock market starts to roll over. Famed trader and fund manager Paul Tudor Jones spoke about this in a rare interview over 15 years ago:

> *My metric for everything I look at is the 200-day moving average of closing prices. I've seen too many things go to zero, stocks and commodities. The whole trick in investing is: "How do I keep from losing everything?" If you use the 200-day moving average rule, then you get out. You play defense and you get out.*

Figure 1: S&P 500 Monthly Bar Chart with 20-Month Moving Average



We certainly do not claim to be the first person to question the viability of the 200-day moving average. According to Mark Hulbert of MarketWatch in an article written in October 2014, the S&P 500 has a fairly decent return since 1990, following breaches of its 200-day moving average.1 He cites Blake LeBaron; a Brandeis University finance professor who found that various moving averages stopped working in the early 1990s.

Within the scope of our own work, we have found the 400-day moving average (and corresponding weekly and monthly moving averages) to be far more effective in recent years in determining support and resistance in various markets. A few examples follow.

Figure 1 plots a monthly bar chart of the S&P 500 over the past 20 years that includes the 20-month moving average. The moving average has been a near perfect trend indicator over the past 20 years. The red arrows show the MA's clean signals, while the blue arrows show the failed signals. We did not include the two recent failed signals. Those notwithstanding, the 20-month moving average has been an excellent indicator and certainly superior to the 10-month moving average (the equivalent of the 200-day moving average).

Figure 2 plots a monthly bar chart of the Morgan Stanley Capital International (MSCI) Emerging Markets Free Index over the past 20 years that includes the 20-month moving average. The 20-month moving average (as support) would have kept a portfolio invested from 2003 until the middle of 2008. It also would have kept you invested into 2011, following the recovery from the global financial crisis. The 10-month moving average or the 200-day moving average gave a handful of sell signals during the 2003 to 2008 period as well as in 2010.

Figure 2: MSCI Emerging Markets Free Index with 20-Month Moving Average

Figure 3: Gold with 20-Month Moving Average

Figure 3 plots Gold, one of the big winners of the current generation along with its 20-month moving average. Note how effective the moving average has been. Once Gold held above the 20-month moving average in late 2001, for the first time in years, it was off to the races. The moving average gave a sell signal in 2008, although Gold only had some downside left and would have left investors whipsawed in the middle of 2012. However, the moving average gave an excellent sell signal at the start of 2013 and kept one out of Gold until only very recently. My personal view is if Gold can hold above the 20-month moving average in the coming months then it will confirm a major trend change.

After considering various tests of moving averages we decided to compare, on a monthly scale, the efficacy and viability of various moving averages as sell signals. In essence, we wanted to know the average decline of a market (and median decline) after it closed below a certain moving average. This could be a way to learn how effective these moving averages are as sell signals. To supplement our study, we tested the 30-month and 40-month moving averages along with the 10-month and 20-month moving averages (which serve as proxies for the 200-day and 400-day moving averages).

Testing moving averages as sell signals makes sense for several reasons. The old adage of market tops are a process and bottoms are an event lends credence to the idea that longer period moving averages may be more effective sell signals. Because market bottoms are an event, shorter moving averages will always outperform in those studies. In addition, studies typically show that the average portfolio performs much better riding the trend rather than trading it. A test of moving averages as sell signals can give us a better idea of when the trend has ended or changed. Our testing shows that the 20-month and 30-month moving averages are the most effective sell signals for the markets tested.

Materials and Methods

To complete the study, we needed monthly price data for the markets we wanted to study. We noted every time the market closed below its 20-month moving average. From that closing price, we calculated the additional decline to its next low. That low was determined be the last low before the market closed back above its 20-month moving average.

We went through the data by hand. The study could also be conducted by someone who knows how to run a program in Excel or another application. Such a study could also look at weekly and daily data.

Results

Here are the results from eight markets. We bold the highest in each column.

S&P 500 (1933–2016)

	Sell Signals (#)	Avg. Decline	Median Decline
10-Month MA	**59**	9.4%	4.0%
20-Month MA	33	**15.6%**	**8.4%**
30-Month MA	31	10.2%	7.2%
40-Month MA	22	11.1%	6.1%

MSCI Emerging Markets Index (1996–2016)

	Sell Signals (#)	Avg. Decline	Median Decline
10-Month MA	**15**	18.7%	8.8%
20-Month MA	9	**24.3%**	**17.1%**
30-Month MA	8	16.6%	14.2%
40-Month MA	8	17.7%	11.8%

Continuous Commodity Index (1956–2016)

	Sell Signals (#)	Avg. Decline	Median Decline
10-Month MA	**46**	6.4%	2.8%
20-Month MA	32	6.3%	3.9%
30-Month MA	28	**6.6%**	**4.1%**
40-Month MA	26	6.3%	2.9%

Gold (1971–2016)

	Sell Signals (#)	Avg. Decline	Median Decline
10-Month MA	**32**	11.5%	6.3%
20-Month MA	19	12.1%	6.4%
30-Month MA	15	12.1%	5.6%
40-Month MA	10	**21.5%**	**25.0%**

Oil (1982–2016)

	Sell Signals (#)	Avg. Decline	Median Decline
10-Month MA	**32**	16.5%	6.2%
20-Month MA	24	**19.1%**	**10.7%**
30-Month MA	23	17.2%	6.2%
40-Month MA	20	14.8%	5.6%

Nasdaq Composite (1978–2016)

	Sell Signals (#)	Avg. Decline	Median Decline
10-Month MA	**31**	9.8%	5.9%
20-Month MA	18	11.3%	5.4%
30-Month MA	13	14.3%	**9.8%**
40-Month MA	9	**15.8%**	9.7%

Hang Seng Index (1969–2016)

	Sell Signals (#)	Avg. Decline	Median Decline
10-Month MA	**35**	17.7%	4.1%
20-Month MA	22	18.1%	**12.5%**
30-Month MA	18	**20.1%**	12.0%
40-Month MA	16	14.8%	3.3%

Nikkei Index (1969–2016)

	Sell Signals (#)	Avg. Decline	Median Decline
10-Month MA	**36**	12.3%	4.6%
20-Month MA	18	18.3%	10.1%
30-Month MA	15	**20.1%**	**12.7%**
40-Month MA	14	18.1%	11.3%

Discussion

The 20-month moving average sell signal (20-MMASS) is most effective for the S&P 500, and by a clear margin. The 20-MMASS occurred 33 times and the average decline was 15.6% with a median decline of 8.6%. This strongly exceeds the 10-MMA sell signal which was triggered a total of 59 times. Its average decline was 9.4% with a median decline of only 4.0%. The 20-MMASS also outperforms the 30-MMA and 40-MMA sell signals, which were triggered 31 times and 22 times respectively. The 20-MMASS outperformed even while it generated more sell signals. The 30-MMASS produced an average decline of 10.2% and median decline of 7.5% while the 40-MMASS produced an average decline of 11.1% and median decline of 6.1%.

As we hinted in the introduction, the 20-month moving average has been an especially more reliable sell signal than the 10-month moving average over the past 20 years. From 1996 to 2016, the 10-month moving average has given a total of 10 sell signals while the 20-month moving average has given five sell signals. Excluding the most recent two signals we find that six of the eight signals from the 10-month moving average were whipsaws while the 20-month moving average produced only one whipsaw. The 10-month moving average would have caused sells in 1998 and 1999 (before the 2000 peak). Traders would have been whipsawed again in 2004 as well as recently in 2010 and 2011.

With regard to emerging markets and their limited history (I have data going back 20 years), the 20-month moving average has proven to be a more effective sell signal than its counterparts. The 20-MMASS produces, from a total of nine signals, the highest average decline and median decline, which are 24.3% and 17.1%, respectively. The 10-MMASS produces 15 signals that generate an average decline of 18.7% and median decline of 8.8%. Both the 30-month and 40-month moving averages produced one less sell signal than the 20-month moving average. Their average declines were 16.7% and 17.7%, respectively, while their median declines were 14.2% and 11.8% respectively.

We should note that because our data starts in 1996, the 30-MMA and 40-MMA miss the sell signal the other moving averages generated in 1997. Even if we estimate that sell signal (visually) and include it in the data for the 30-month moving average, the 20-month moving average remains superior. Including that missed signal, the average decline of the 30-month moving average becomes 21.1%, which remains below the average of the 20-month moving average signals. The median decline becomes 14.4%, still below the median decline of the 20-month moving average.

The superiority of the 20-month moving average as a sell signal is typified by the period from 2001 to 2011. That, of course, was a boom period for emerging markets, excluding the global financial crisis. During the 2001 to 2011 period, the 10-month moving average gave a total of seven sell signals to only two from the 20-month moving average. The 10-month moving average would have whipsawed longs in 2004, 2006, several times in 2008, and then in 2010.

The individual indices we examined did not produce the same results as the S&P 500 and Emerging Markets index. However, it was not the 10-month moving average that produced the most reliable signals, but the much larger period moving averages. For the Nikkei index (Japan), we examined over 45 years' worth of data and found the 30-month moving average on average produced the most reliable sell signals. The 30-MMASS occurred 15 times and registered an average decline of 20.1% and a median decline of 12.7%. Both the 40-month and 20-month moving average signals produced averages and medians that were slightly less than those of the 20-MMA.

The Nikkei's poor long-term performance could explain why sell signals from the longer period moving averages generated better results than the 20-MMASS. At present the Nikkei is trading at the same level as 1986! That is the same price as 30 years ago! That means that the Nikkei has spent quite a lot of time testing and falling below longer period moving averages. In relative terms, it has spent far more time doing so than the S&P 500 and Emerging Markets.

While Hong Kong has not struggled the way Japan has, its Hang Seng index is only trading slightly above its 2000 peak. Like the Nikkei, the Hang Seng's 30-MMASS produces the highest average decline at 20.1%. However, the 20-MMASS is a close second at 18.1% and produces the highest median decline at 12.5%. Interestingly, the 10-MMASS has a higher average decline (17.7% to 14.8%) and higher median decline (4.1% to 3.3%) than that of the 40-MMASS, which has less than half of the sell signals. The explanation for that result could be the relatively strong historical trend of the Hang Seng yet its proclivity for sudden sharp declines.

The Nasdaq Composite is somewhat similar to the Hang Seng, as it has a tendency for severe bear markets, has performed well over time, and is trading around its 2000 peak. Interestingly, both the median and average decline is highest for the multi-year moving averages. The 40-MMASS produces the highest average decline at 15.8%, while its median decline of 9.7% is eclipsed by the 9.8% median decline of the 30-MMASS. The 30-month moving average produces 13 sell signals compared to only nine from the 40-month moving average.

Turning to the asset class of commodities, and viewing the data through the lens of the continuous commodity index (which was the CRB until 2005), we find little variation between the four moving averages. The average decline from each sell signal falls into a range of 6.3% to 6.6%, while the median decline ranges from 2.8% to 4.1%. Unlike equities, commodities do not consistently trend higher over time. Hence, there is a large amount of sell signals from 30-month and 40-month moving averages relative to the other markets studied.

It is interesting to note that Oil and Gold, the two most widely followed commodities show completely different results than the commodity sector as one market. For Gold, the 40-month moving average produced the best sell signals, as its average decline was 21.5% and its median decline was 25%. Both figures dwarf the data for the other three signals, which are fairly similar. The 10-MMASS, 20-MMASS and 30-MMASS produced median declines from 5.6% to 6.4% and average declines of 11.5% to 12.1%. For oil, the 20-month moving average produced the highest readings, which were an average decline of 19.1% and median decline of 10.7%.

The differing results between Oil and Gold are not a surprise if examining their history closely. From afar their performance looks similar. However, there are a few key differences. Gold has spent most of its time in rip-roaring bull markets and significant bear markets. The times it lost its 40-month moving average it tended to stay below it for quite a while. Oil is different because it has had more frequent booms and busts that caused more sell signals. Oil had fewer years of data but more sell signals in every category.

Conclusion

The objective of this study was to research the efficacy of the 400-day moving average (using the 20-month moving average as our proxy) as a sell signal in order to potentially raise its importance and diminish the importance of the 200-day moving average (using the 10-month moving average as its proxy). To examine the efficacy of moving averages as a sell signal, we tabulated the decline in the market (being studied) after it closed below four moving averages: the 10-month, 20-month, 30-month and 40-month moving averages. We studied a total of eight different markets, which included five equity markets and three commodity markets. The markets were as follows: S&P 500, Morgan Stanley Emerging Markets Index, Nasdaq Composite, Hang Seng, Gold, Oil and the Continuous Commodity Index.

There were some similarities in the results but also differences between asset classes and markets alike. The most notable similarity was that the first two markets we studied—arguably the two most widely followed indices from a U.S. vantage point (S&P 500 and the Morgan Stanley Emerging Markets Index)—had very similar results. For both, the average and median decline from the 20-month moving average sell signal outperformed all other signals. The most striking difference was the variation in the results between those aforementioned indices and the other indices we tested, such as the Nasdaq Composite, the Hang Seng and the Nikkei.

Other than for the S&P 500 and Emerging Markets, there was little uniformity in the most effective sell signal for equities. The data from those indices argues that it is the 20-month moving average sell signal, while the data from the other markets is mostly scattered between the 30-month moving average and 40-month moving average signals. That could be the result of the Nikkei's poor long-term performance and the vicious bear markets endured by both the Hang Seng and Nasdaq Composite.

Speaking of vicious bear markets, the most bizarre data came from the continuous commodity index, but not the individual commodities we studied. There was almost no difference between the four sell signals for the continuous commodity index. The four signals ranged from 6.3% to 6.6% for average decline and from 2.8% to 4.1% for median decline. Both highs were from the 20-month moving average signal.

Meanwhile, data from Gold and Oil showed no similarity to each other or that from the larger commodity index. The 20-month moving average sell signal produced the highest number for both the average decline and median decline. Gold was the true outlier in the study as it was the only case where the 40-month moving average sell signal produced the highest number for both the average and median decline. And it wasn't even close.

Ultimately it is foolish to think that any single moving average is uniform as the best or most effective sell signal. It depends on the market being studied, its history, and what stage that market is in. For example, breaking the 20-month moving average is more significant if it occurs after an aging bull market than if it occurs when the market is trying to bottom after a well entrenched bear. The data shows it is more significant if it occurs in the S&P 500 or a market with broad constituents like the MSCI Emerging Markets Index as compared to an individual index that tends to have greater swings. We can say that our data makes a strong case that depending on the market, either the 20-month moving average or 30-month moving average is a better sell signal than the 10-month moving average.

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Notes

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Price Rotation Around Pyramid Cones Theory and Square of Nine Bands Indicator and Oscillator

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Abstract

Looking at the pyramid cone, we will find that it contains a lot of interesting facts. Let us consider the Great Pyramid that was built by ancient Egyptians. If we take a plan picture of it, we will see what is referred to the Square of Nine, which is the tool that was utilized by W.D. Gann[1] and which we are going to focus on in details within this thesis.

This research is trying to solve the problem of anticipating the start and end of the trend fluctuations. This will be done through introducing a new theory for the price movement based on numerical rotations around pyramid cones. This theory will also help in forecasting price targets and determining trend strength. By the end of this research and by using the tenets of this theory dynamic indicators have been created which are the "Square of Nine Bands" and "Square of Nine Oscillator".

Introduction

An extremely interesting methodology was introduced by W.D. Gann[1] called the Square of Nine. This methodology has opened the gates to a totally different perspective in analyzing the price action, as it plots the price chart different to the other familiar technical analysis tools. W.D. Gann introduced the Hexagon Chart[2] and Circle of 24 Chart.[3] Those charts were then developed based on the same W.D. Gann's concept to create the Pentagon Chart, Heptagon Chart, Octagon Chart and Nonagon Chart. The purpose of this research is to examine and collect the tenets and logic behind what W.D. Gann used in order to create such a tool by introducing a new theory that is called hereafter "Price Rotation Around Pyramid Cones Theory". One of the main references that this research is going to rely on is the book by Patrick Mikula, *The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine*, which describes and explains the way the Square of Nine is used in forecasting the price action.

After illustrating the Price Rotation Around Pyramid Cones Theory types of pyramids and pyramid charts, the thesis will move on to explain the applicability of this theory by using what is called by Patrick Mikula "The Square of Nine" and the use of angle and shapes overlay in forecasting the next price movement and important support and resistance levels.

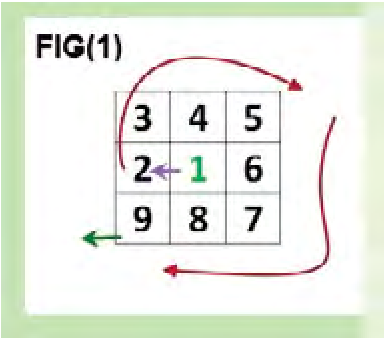
The fourth part will reveal my contribution in making some modifications to the Square of Nine tool by using the moving average concept. This will create two new types of indicators that will be referred to as "The Square of Nine Bands" and "The Square of Nine Oscillator". I will facilitate the understanding of those indicators and show practical examples on how to use them on the Metastock program using its programming language and explaining all the requested inputs. Finally, the thesis will illustrate practical examples in how to use those indicators in determining trend types, strength and targets.

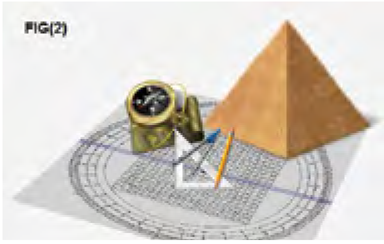
Price Rotation Around Pyramid Cones Theory

Price movements consist of a series of consecutive increments that are following the numerical rotation around pyramid cones starting from their tops toward their bottoms in rows or layers with every layer wider than its previous one until reaching the last layer in the bottom or basement. Every layer or row consists of a specific number of cells as every cell is identified by a unique cell number that is loaded by specific price value according to the pyramid type and cell increment. Layers or rows are also divided by specific angles that are crossing important cells that affect the numerical rotation or price movement.

The previous paragraph is the conclusion of collecting what W.D. Gann stated and developed in his books to create a new theory called "The Price Rotation Around Pyramid Cones Theory".

Figure 1 and Figure 2. The Price Rotation Around Pyramid Cones Theory





To be able to understand the way we reach this theory we must first understand pyramid types.

Types of Pyramids

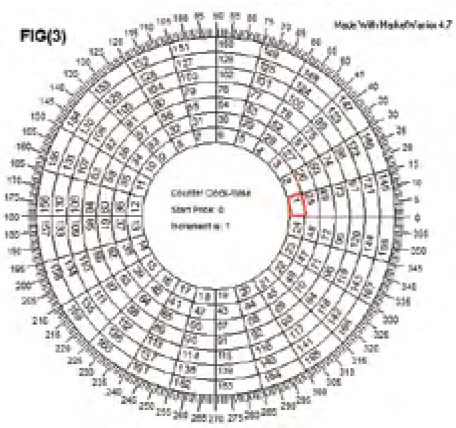
- Circle Pyramid
- Square Pyramid
- Pentagon Pyramid
- Hexagon Pyramid
- Heptagon Pyramid
- Octagon Pyramid
- Nonagon Pyramid

Every type of these pyramids has its unique cell distribution in its rows or layers, and every cell has its unique number that is loaded with its specific price value. We have to know price increment value to multiply it by cell number to calculate the cell value. If we draw plan pictures of the pyramid cones as if we are looking to it from the top, we will get all the next types of charts. Some of these charts, like Square of Nine, Hexagon, and Circle of 24, were used by W.D. Gann, and the rest were deduced based on the main concept of charting structure. W.D. Gann didn`t mention the logic behind the structure of his Square of Nine and its interaction with human psychology, but surely his methodology was a reflection to price rotation around conic geometrics because W.D. Gann mentioned in one of his books *The Tunnel Thru the Air* this sentence: "In making my predictions I use geometry and mathematics just as an astronomer, based on immutable laws."[4] Also, this point of view was confirmed later by Mr. Daniel Ferrera. Daniel Ferrera in his new course The Gann Pyramid: Square Of Nine Essentials beautifully describes the various functions of the Square of Nine as a mathematical and astronomical calculator. He also points out that the Square of Nine is not to be perceived in only its two-dimensional perspective but as a pyramid spiraling from the center around and down to the outer ring at the base of the pyramid. This ties in nicely with our understanding of natural growth and its relationship to the extension of the universal vital principle called "Brahma" through the lotus temple or market. Manifest form projects itself into the three dimensions of space and time in the form of a three-dimensional conic, not a two-dimensional spiral. Therefore we should perceive the growth of our form taking on extension in the Z-plane forming a vortex, whirlpool, or conic spiral as it rotates through the mathematical grid of planetary and stellar influences. India is not the only ancient civilization to have possessed this subtle wisdom. Again, in Ancient Egypt we find the same design built into the ground plan of the Great Pyramid.[5]

Types of Pyramid Charts

Circle of 24

Figure 3. Circle of 24 Chart



In this type, every row or layer is divided into 24 cells, which means that every part is 15 degrees cell numbering is rotating counter-clockwise and spacing between each row is constant = 24 cells (e.g., 25-1=24 and 49-25=24 degrees is starting from the right at watch 3 counter-clockwise).

Formula of moving around circle of 24.

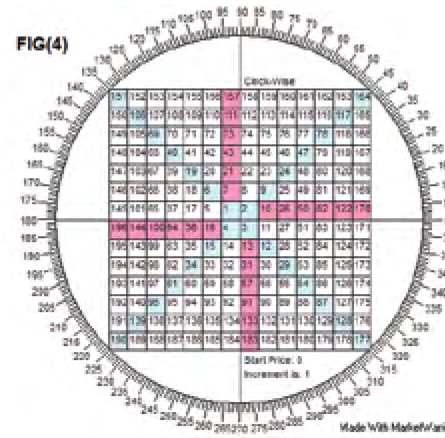
To increase starting cell no. by a complete one rotation = (cell no.+24) * increment

To decrease starting cell no. by a complete one rotation = (cell no.-24) * Increment

For example, to add one complete rotation from cell number 79 = (79+24)*1 = 103

Square of Four

Figure 4. Square of Four Chart



In this type, the top layer zero consists of four cells, and the next layer consists of 12 cells, ending with cell no. 16 and so on. No. of cells in layer = (layer no. +1) * 4

Formula of moving around square of 4

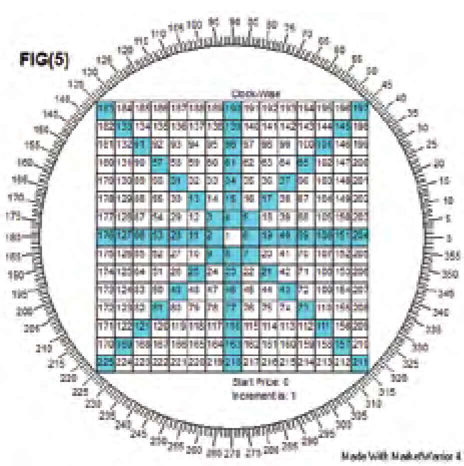
To increase starting cell no. by a complete one rotation ≈ (Square root (Cell no.* Increment) + 1.999) ^2

To decrease starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)-1.999) ^2

For example, to add one complete rotation from cell number 79 ≈ ((square root(79*1)+1.999)^2 ≈ 118.53

Square of Nine

Figure 5. Square of Nine



In this type, the top layer zero consists of only one cell, and the next layer is eight cells ending with cell no. 9 and so on. No. of cells in a layer = layer no.* 8 example the layer no. 7 that is ending with 225 is containing 7*8= 56 cells exactly 225-169 =56 cells, and we will discuss this type later in full detail.

Formula of moving around Square of Nine

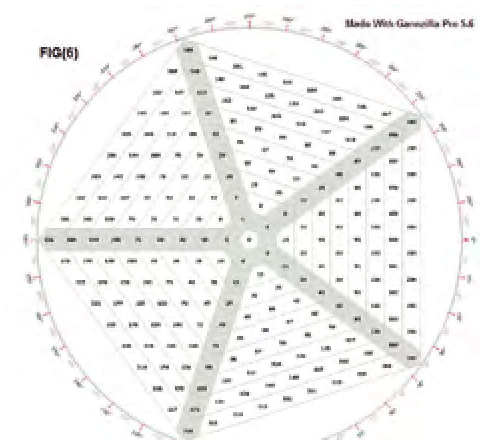
To increase starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)+ 1.999) ^2.

To decrease starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)- 1.999) ^2

For example, to add one complete rotation from cell number 79 ≈ ((square root(79*1)+1.999)^2 ≈ 118.53

Pentagon

Figure 6. Pentagon Chart



In this type, layer zero or the top consists of just no cell, the next layer consists of five cells ending by cell no. 5, so we can say that any layer is containing a number of cells = layer no. *5 example layer no. 5 which ending with cell no. 75 is containing = 5*5 = 25 cells the same value = 75-50 =25 and so on.

Note that the outer degree is clockwise, as it doesn`t make any difference if you fixed all your works to be clockwise, so the result will be the same.

Formula of moving around Pentagon

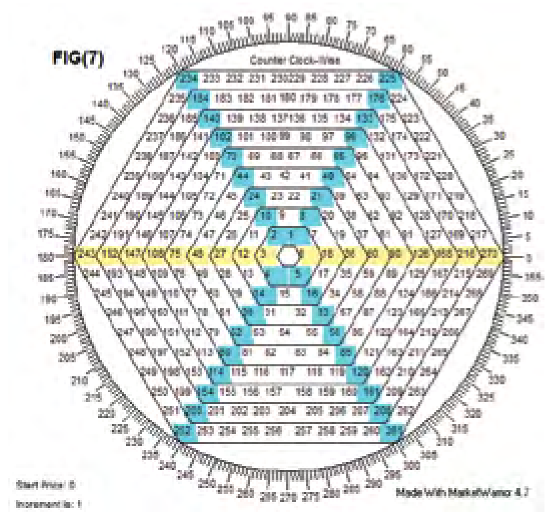
To increase starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)+1.581) ^2.

To decrease starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)- 1.581) ^2

For example, to add one complete rotation from cell number 79 ≈ ((square root(79*1)+1.581)^2 ≈ 109.6

Hexagon

Figure 7. Hexagon Chart



In this type, the top or layer zero consists of only no cell, then the next layer consists of six cells ending by cell no. 6. Then, each layer consists of a variable number of cells = layer no. *6 example no. of cells in the layer that is ending by cell no. 126 =6*6 =36 cells the same value = 126-90= 36 cells.

Formula of moving around Hexagon

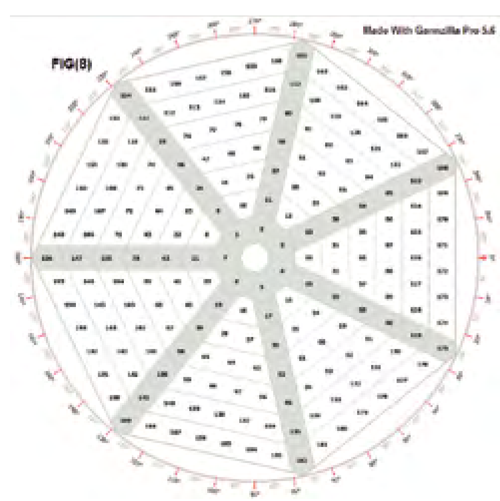
To increase starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)+1.732) ^2

To decrease starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)-1.732) ^2

For example, to add one complete rotation from cell number 79 ≈ ((square root(79*1)+1.732)^2 ≈ 112.8

Heptagon

Figure 8. Heptagon Chart



In this type, layer zero or the top has no cell and then the next layer consists of seven cells as we calculate the number of cells in any row = layer no. * 7 and so on.

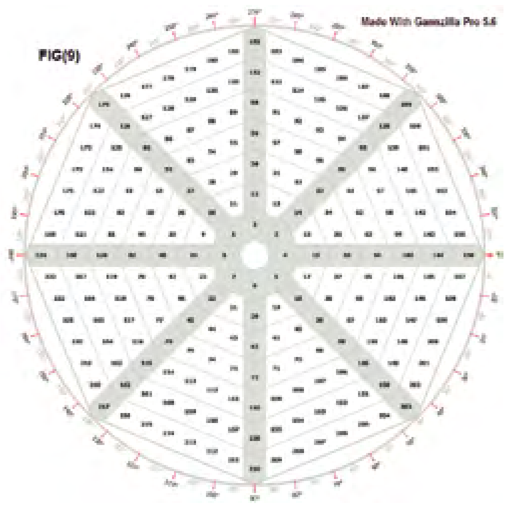
Formula of moving around Heptagon
To increase starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)+ 1.870) ^2.

To decrease starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)-1.870) ^2

For example to add one complete rotation from cell number 79 ≈ ((square root(79*1)+1.870)^2 ≈ 115.7

Octagon

Figure 9. Octagon Chart



In this type, layer zero or the top has no cell and then the next layer consists of eight cells as we calculate the number of cells in any row = layer no. * 8 and so on.

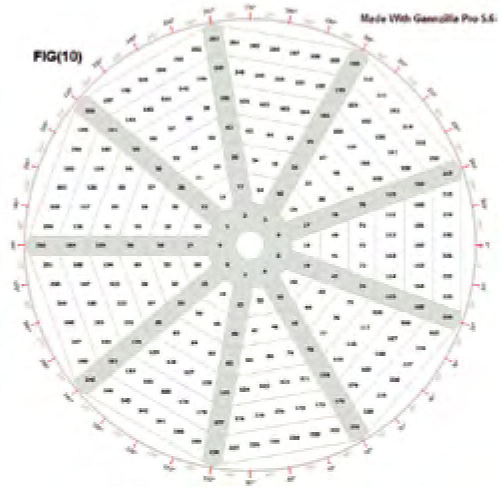
Formula of moving around Octagon.
To increase starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)+ 1.999) ^2.

To decrease starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)- 1.999) ^2

For example to add one complete rotation from cell number 79 ≈ ((square root(79*1)+1.999)^2 ≈ 118.53

Nonagon

Figure 10. Nonagon Chart



In this type, layer zero or the top has no cell and then the next layer consists of 9 cells as we calculate the number of cells in any row = layer no. * 9 and so on.

Formula of moving around Nonagon
To increase starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)+ 2.121) ^2

To decrease starting cell no. by a complete one rotation ≈ (Square root(Cell no.* Increment)- 2.121) ^2

For example to add one complete rotation from cell number 79 ≈ ((square root(79*1)+2.121)^2 ≈ 121.2

By studying all previous chart types except Circle of 24, we will notice that there is a common formula for increasing a complete one rotation, which is

(Square root (Cell no.* Increment) + Factor) ^2

And a common formula for decreasing one complete rotation, which is

(Square root (Cell no.* Increment) - Factor) ^2

The "Factor" is changeable according to chart type. Some charts have almost the same factors, which are the Square of Four, the Square of Nine, and the Octagon, which is almost equal to 1.999. That is why W.D Gann gave more weight to Square of Nine than any other type, because it has approximately the same rotation factor that is used by the Square of Four and the Octagon. In other words, the Square of Nine includes the three types of charts (Square of Nine, Square of Four, and the Octagon). This is why the paper will focus on the Square of Nine and try to reveal its secrets!

The Trading Fives website mentioned this paragraph, which confirms the concept of rotation formula in a book titled *Trading the Square of Nine with a Calculator and Pencil:*

"A book titled *The Templeton Touch* by William Proctor disclosed that one of Templeton's 22 principles for stock market investing was that stock price fluctuations are proportional to the square root of the price. Square roots will always maintain a cozy mainstream relationship with stock prices if only because they are an essential component of almost every volatility or option pricing formula. The theory holds that stock prices move over the long and short term in a square root relationship. For example IBM made a monthly closing low of 4.52 in June, 1962 and monthly closing high of 125.69 in July, 1999. This is within a few percentage points of the square of the sum of the square root of the low price + 9 or (2.12+9)^2. GM made a low of 15 in November, 1974 and a high of 95 in May, 1999. Again, a few percentage points from the square of the sum of the square root of the low + 6 or (3.87+6)^2. There are hundreds and hundreds of these examples across the stock, financial and commodity markets. Even a few minutes with a pile of stock charts and a calculator will build confidence that major highs and lows are related to each other by additions and subtractions to their square roots. The Square of Nine takes these square root relationships to a different level as you will learn in the pages ahead."

"We use the square of odd and even numbers to get not only the proof of market movements but the cause" (W. D. Gann, *The Basis of My Forecasting Method* (the Geometrical Angles course), p.1.[6]

Square of Nine

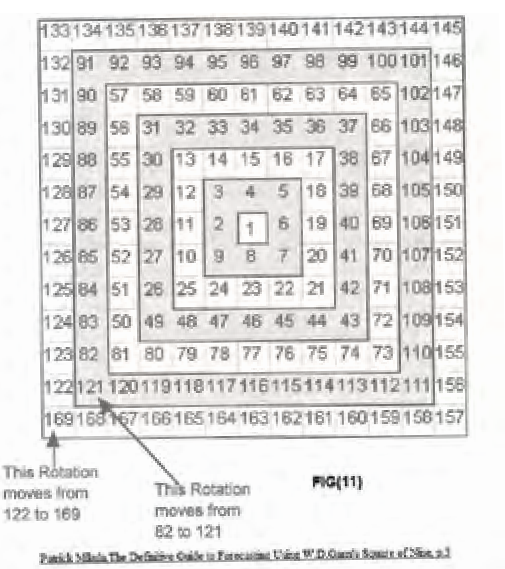
Before we continue with our illustration, it is important to know some information about W.D. Gann. He was a financial advisor and trader in the stock and commodity markets during the first half of the 20th century. In the 1920s, he developed the Square of Nine as a financial tool for trading and forecasting. Methods of using it were taught by W.D. Gann in his private financial seminars and written trading courses. In his later books, he started to use Circle of 24 and Hexagon. In the following paragraphs, the basic concepts that those charts are drawn upon are going to be explained.

Complete Cycle Rotation:

W.D. Gann used the words "Square" and "Cycle" when referring to 360 degrees movement around the Square of Nine

Figure 11 shows the movement from 50 to 81 as one 360 degree movement, or one complete cycle rotation.[7]

Figure 11. 360 Degree Movement Around the Square of Nine



The reason behind the name "Square of Nine":

In Figure 12, it can be noticed that every circled cell is an odd square number and the first odd square number is 9, which is equal to 3*3 and which also comes after the first complete rotation; thus, the square is called by its cell number "Square of Nine".[8]

In the upright side in the next figure (Figure 13), it can be clearly seen that all circled cells are even squares.[9]

Figure 12. Origin of "Square of Nine"

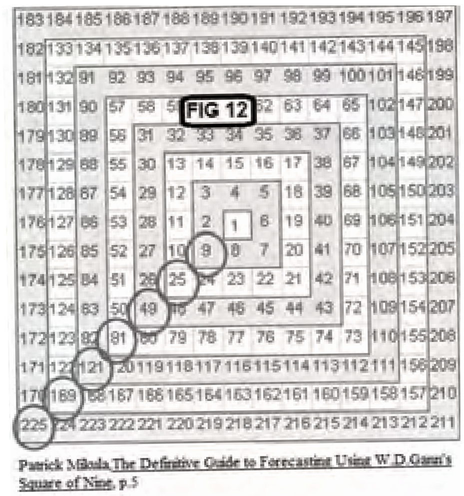
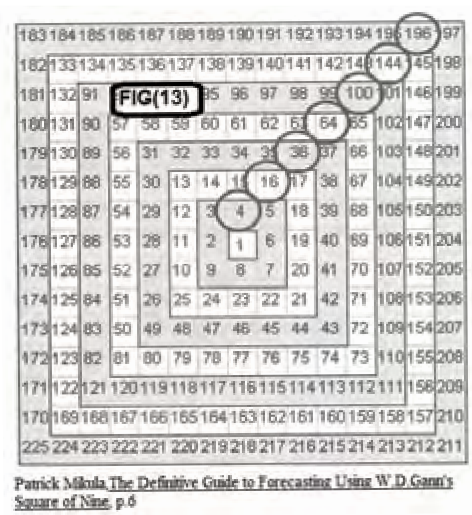


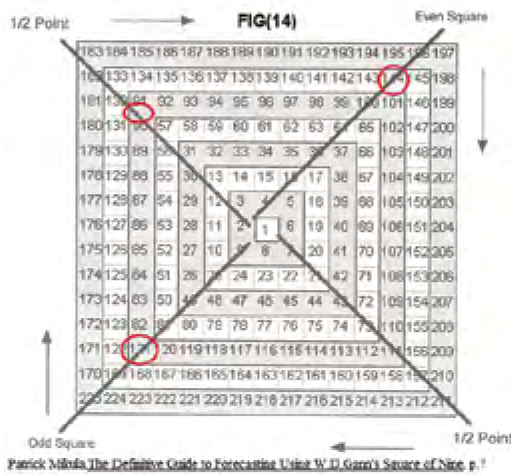
Figure 13. Circled Cells Are Even Squares



Square Number Halfway Points:

In Figure 14, for example, we will find that 121 is the square of 11 and 144 is the square of 12, so the half point line is crossing the rotation path at approximately 90.5, which is considered 11.5*11.5 and the same at the opposite direction.[10]

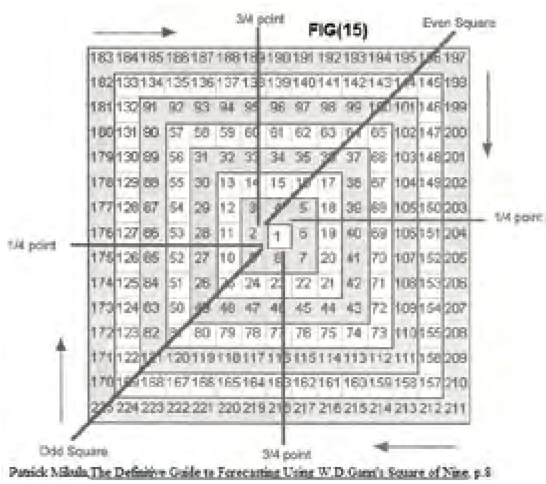
Figure 14. Square Number Halfway Points



Square Number Quarter Points:

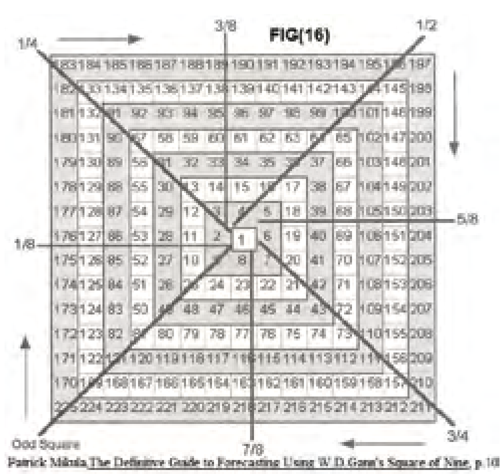
In the following shape, we divide the previous shape by 2 to have 1/4 square number points.[11]

Figure 15. Square Number Quarter Points



By collecting all these types of dividing square points, we will get the following shape in Figure 16, where every point represents one-eighth increments around full rotation.[12]

Figure 16. Every Point Represents One-Eighth Increments



All these evidences prove why W.D Gann provided us the rule that cells that fall on the diagonal cross and cardinal cross are important for market analysis.

As an example, we can look back at Figure 5 of the Square of Nine, which shows that 360/8 = 8 angles 45,90,135,180,225,270, 335,360[13]

We can also notice that when the rotation widens, the value added by every complete rotation increases. For example, at 90 degrees, the value added to 1 in order to be = 4 is 3.

The value added to 4 in order to be = 16 is 9. Value added to 15 in order to be = 34 is 19. On the other hand, we will notice that the rate of change is decreasing. For example, at 90 degrees, the rate of change from 1 to 4 = 300%; the rate of change from 4 to 15 = 175%; the rate of change from 15 to 34 = 127%.

Angle Overlay and Shapes Overlay

There are two types of overlays used with Square of Nine. Figure 17 shows the angles from the cardinal cross and diagonal cross.[14]

There is a fixed angle in the Square of Nine as we mentioned before, but there are dynamic angles that we can overlay to start counting from any angle on the Square of Nine.

For example, Figure 18 uses zero degrees at 212 degrees, so all cardinal cross and diagonal cross will be related to 212.

Figure 17. Cardinal and Diagonal Cross

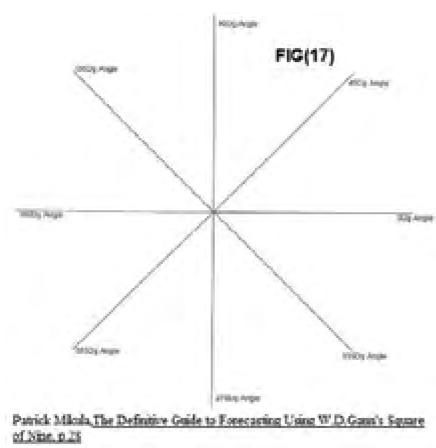
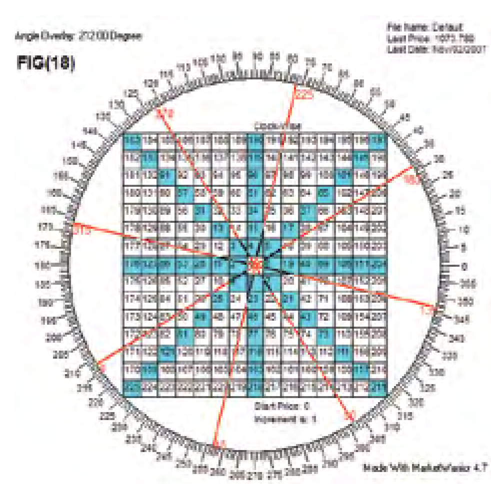


Figure 18. Cardinal and Diagonal Cross Related to 212



W.D. Gann also used overlays with angles every 60 degrees, like the examples in Figures 19 and 20.

Figure 19. Overlay Every 60 Degrees

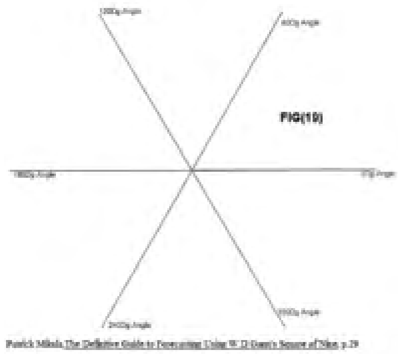
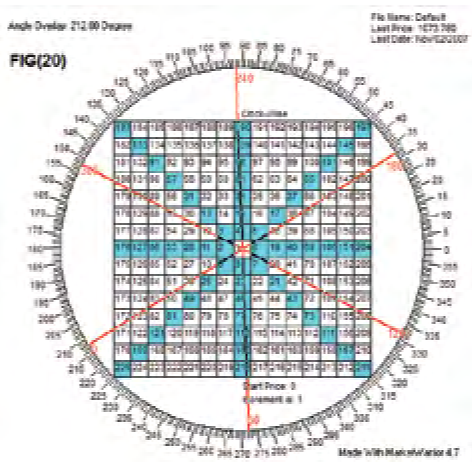


Figure 20. Overlay Every 60 Degrees



To summarize, angle overlays and shape overlays are dividing the Square of Nine by the following sequence:

1. Octagon overlay divides the cycle into 8 angles, every one equal to 45 degrees: 45, 90, 135, 180, 225, 279, 335, 360.
2. Heptagon overlay divides the cycle into 7 angles, every one equal to 360/7: 51.43, 102.86, 154.29, 205.7, 257.14, 308.57, 360.
3. Hexagon overlay divides the cycle into 6 angles, every one equal to 60 degrees: 60, 120, 180, 240, 300, 360.
4. Pentgon overlay divides the cycle into 5 angles, every one equal to 72 degrees: 72, 144, 216, 288, 360.
5. Square overlay divides the cycle into 4 angles, every one equal to 90 degrees 90, 180, 270, 360.
6. Triangle overlay divides the cycle in 3 angles, every one equal to 120 degrees: 120, 240, 360.

From the results above, which includes all angle overlays and shape overlays that are considered two sides of the same coin[15], we can conclude that every market and security has its unique nature that may be matched well with a specific shape overlay. The cycle may be repeated more than one time (whether it was a complete or partial cycle). Prices also can make a double cycle by rotating 720 degrees or 1.5 cycle by rotating 540 degrees or 2.5 cycle rotating 900 degrees. The analyst can choose the shape overlay that matches the price action.

W.D. Gann believes that every market has its own personality, and each market has its own amount of movement around the Square of Nine.[16] This proves that the selected shape overlay tends to last and continue for a long time with its security, and it never changes randomly except in very rare cases.

An important note is that active cycles may be repeated more than one time in case of extreme price movements. For example, if in normal price movement, the price action is trying to reach 1.5 cycles, or 540 degrees of rotation, in some extreme cases it could reach double or triple this move, which means that it will reach 3 cycles (2*1.5) or 4.5 cycles (3*1.5).

The idea that every reaction is equal to its action should be also applied. For example, if prices normally advance by a (270 degrees) 0.75 cycle, if it then declines breaking its starting point, prices are expected to decrease by (270 degrees) 0.75 cycle.

This point will be discussed intensively in the section about applying the Square of Nine Bands and Square of Nine Oscillator.

Forecasting Prices Via Cell Number[17]

The used Square of Nine with price increment = 100.

The selection of the price increment depends on the chart price value and timeframe, and therefore its volatile nature. The following example is of EGX30, the Egyptian stock market index on a monthly basis. It can be noticed that the important and significant support and resistance levels are coming from 90 and 225 degrees and sometimes from 270 degrees, as can be seen in Figures 21 and 22. Cell no. 34, 61, 96 at 90 degrees and 49, 81, 121 are all plotted in Figure 21.

Figure 21. EGX30 on a Monthly Basis

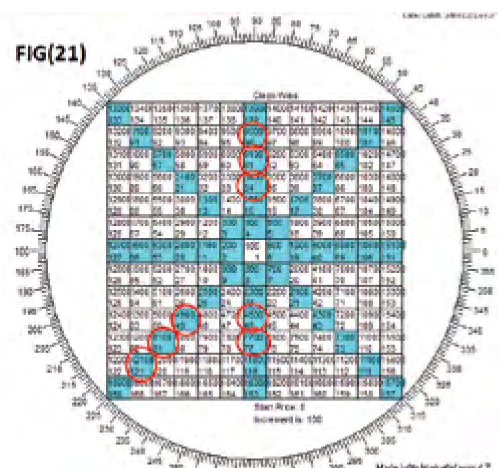


Figure 22. EGX30 Monthly Chart

Forecasting Prices Via Overlays[18]

Figures 23 and 24 are of the Dow Jones Index, and Square of Nine of increment equal 100 is going to be used.

The bottom of 2002 (7181) is plotted in the Square of Nine. Cells that are located at 240 degrees from the plotted point are forming a clear resistance area; thus, the Triangle overlay can be used in the future forecasting.

Figure 23. Dow Jones Index on a Monthly Basis

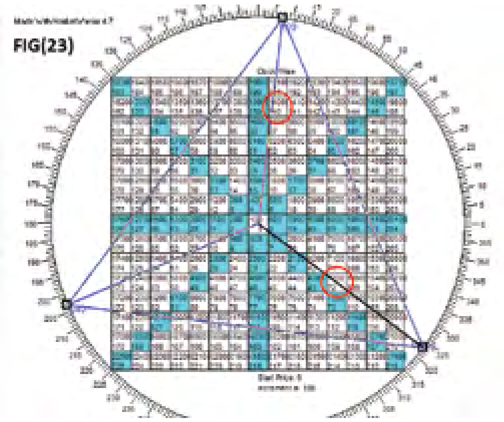


Figure 24. Dow Jones Index Monthly Chart

Based on this analysis, the 240 degree overlay is expected to remain working as a resistance area. The following figures will show the future action.

In figure 25, the low of 2009 (6440) is plotted on the Square of Nine, and the overlay will be a Triangle.

Based on this analysis, the 240 degree will act as a clear resistance in the future that will face all the circled cells.

Figure 26 illustrates how the market really acted during this period.

Figure 25. Dow Jones Index on a Monthly Basis

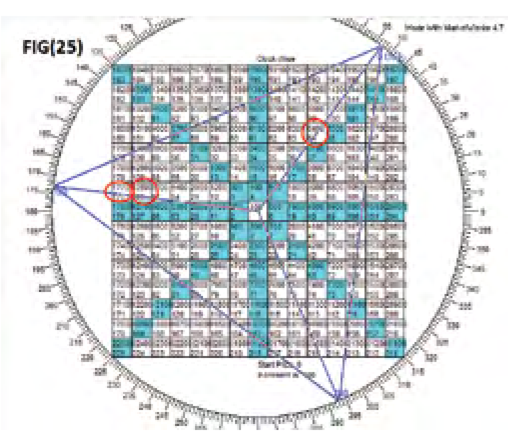
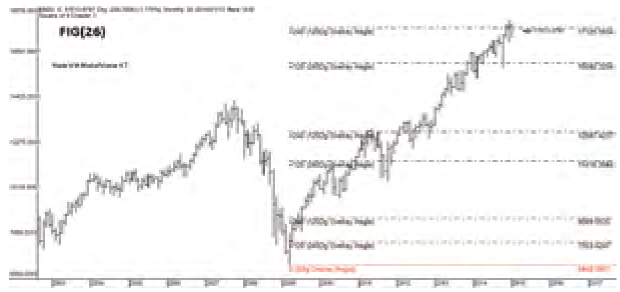


Figure 26. Dow Jones Index Monthly Chart



The Idea and The Logic Behind the Square of Nine Indicator

From the explanation given in the previous examples, to get the cycle target, a specific shape is added on the price movement that was calculated from overlaying the low in the Square of Nine. The new idea is to replace the low by a value that represents the 20 days ago lows; thus, a 20-day exponential moving average is calculated for the lows. On the other hand, in the case of price decline, the highest high value will be plotted in the Square of Nine; the shape that matches with the overlay will be selected; the decreased value of the cycle will be calculated, thus replacing this high by a value that represents the 20 days ago highs; and the 20-day exponential moving average for the highs will be calculated.

Then, it is suggested to have a Median Line = (EMA20(high)+EMA20(low))/2.

If the price closes above the Median Line, this infers that it is targeting the increased cycle, and if it closes below the Median Line, this infers that it is targeting the decreased cycle.

The Upper Primary Band is the target that is calculated from the rotation of the EMA20 (low) of one increased complete cycle of 360 degrees (default value may be changed by the analyst based on the nature of the chart price movement).

The Upper Secondary Band is the target that the price is going to reach if it succeeds in breaking above the Primary Upper Band. It is calculated from the rotation of the EMA20 (low) with double primary increased cycle, and this level of pricing is considered an extreme level that the price may retrace from it at any time. The movement to continue between Primary Upper Band and Secondary Upper Band shows strength of buyers or a very strong uptrend, and failing to reach the Primary Upper Band is considered an alarm of weakness in the purchasing power.

The Lower Primary Band is the target that is calculated from the rotation of the EMA20 (low) of one decreased complete cycle of 360 degrees (default value may be changed by the analyst based on the nature of the chart price movement).

The Lower Secondary Band is the target that the price is going to reach if it succeeds in breaking below the Primary Lower Band. It is calculated from the rotation of the EMA20 (low) with double primary decreased cycle, and this level of pricing is considered an extreme level that the price may rebound from it at any time. The movement to continue between Primary Upper Band and Secondary Upper Band shows strength of sellers or a very strong downtrend, and failing to reach the Primary Lower Band is considered an alarm of weakness in the selling power.

Square of Nine Bands

Square of Nine Bands consists of 5 lines:

- Median line
- Primary upper band
- Primary lower band
- Secondary upper band
- Secondary lower band calculation of Square of Nine Bands

Calculate exponential moving average 20 for the lows of the bars = EMA20 (Low) Calculate exponential moving average 20 for the highs of the bars =EMA20 (High) Multiplied EMA20 (Low) = EMA20 (Low)* Multiplier Multiplied EMA20 (High) = EMA20 (High)* Multiplier

Median Line = (EMA20(High)+EMA20(Low))/2 Primary Upper Band =

((Square root(Multiplied EMA20(Low))+1.999*Θ/360)^2)/ Multiplier where Θ is the rotation angle Primary Lower Band = ((Square root (Multiplied EMA20(High))-1.999*Θ/360)^2)/ Multiplier where Θ is the rotation angle

Secondary Upper Band= ((Square root (Multiplied EMA20(Low))+1.999*2*Θ/360)^2)/Multiplier where Θ is the rotation angle Secondary Lower Band = Square root ((Multiplied EMA20(High))-1.999*2*Θ/360)^2)/ Multiplier where Θ is the rotation angle

If Θ = rotation and Secondary bands will represent two complete rotation or two complete cycles.

360 or complete one rotation, the Primary bands will represent the one complete.

Square of Nine Oscillator

This indicator is extracted from the Square of Nine Bands to enhance the trading tactic. Its idea is to measure the percent of achievement that the price action scores in reaching upper bands, in the case of moving to the upside, or reaching lower bands in the case of moving to the downside. The word percent refers to degrees percent.

For example, reaching the primary upper band means that price action succeeded reaching 100% of the permitted target, and so if the defined cycle is assigned to be 360 degrees, this action is translated to be drawn as 360 degrees in the oscillator. If Θ = 360 of complete one rotation the primary bands, it will represent the one complete rotation, and secondary bands will represent two complete rotation or two complete cycles.

Calculation of Square of Nine Oscillator:

Oscillator Value Case (1) Close > Median Line

a. High <= Primary Upper Band Oscillator Value = (difference between the High and EMA20(LOW)) / (difference between the EMA20(LOW) and Primary Upper band)*Θ
b. High > Primary Upper Band Oscillator Value = (difference between the High and EMA20(LOW)) / (difference between the EMA20(LOW) and Secondary Upper band)*2*Θ

Case (2) Close<Median Line

a. Low >= Primary Lower Band Oscillator Value = (difference between the Low and EMA20(HIGH)) / (difference between EMA20(HIGH) and the Primary Lower band)*Θ
b. Low < Primary Lower Band Oscillator Value = (difference between the Low and EMA20(HIGH)) / (difference between EMA20(HIGH) and Secondary Lower band)*2*Θ Where Θ is the rotation angle of the used Cycle

All basic rules of interpreting indicators can be used with this oscillator as a leading indicator starting from divergences and failure swings, etc.

Metastock Application

The trading system using these indicators will be applied using the Metastock software.

1. The angle rotation of the cycle after overlay occurred
2. The value of the EMA which is used in calculating median line
3. Multiplier value is calculated from the selected increment that is used in the Square of Nine, Multiplier = 1/Increment
4. It is set by default to Square of Nine Chart (Circle of 24 =0,1 = Square Of Nine or Square of Four or Octagon, 2 = Pentagon , 3 = Hexagon , 4 = Heptagon , 5 = Nonagon)[19]

How to Set Increment Value:

Increment = 1/Multiplier

As mentioned before, it is a subjective value that can be set by the analyst upon his point of view based on the chart pricing value and the chart volatility, but it is recommended to use the following guide. Still, the analyst may change these values upon his visual inspection and chart testing.

The multiplier may be set to be equal to any of these values: 0.01, 0.1, 1, 10,100. The analyst may replace one of these values with another to reach the best value that matches the price volatility.

We have to notice that selecting multiplier = 0.01 means that the increment used = 100, so cell counting will be 100, 200, 300, and so on. Thus, low sensitivity values will be obtained, but it is better to use with high price movement ranges.

On the other hand, selecting multiplier = 10 means that the increment used = 0.1, so cell counting will be 0.1, 0.2 , 0.3 and so on. Thus, high sensitivity values will be obtained, but it is better to use with low price movement ranges.

How to Set Rotation Angle:

As mentioned before, rotation angles are deduced from angle overlay or shape overlay. The analyst may select the one of deduced divided angles according to his/her selected shape overlay (40, 45, 60, 72, 90, 120, 135, 144, 180, 216, 225, 270, 288, 315, 360).

The analyst may replace one of these angles with another until he/she gets the best angle that matches the price chart movement (The upper and lower primary bands are acting as significant support and resistance levels historically on the chart).

Trend Identification

Identification of the current price trend will be as follows:

a. Sideways, when price is moving most of the time between Primary Upper Band and Primary Lower Band.
b. Uptrend, when the price is moving most of the time between Median Line and Primary Upper Band.
c. Strong uptrend, when price is moving between Primary Upper Band and Secondary Upper Band.
d. Downtrend, when price is moving most of the time between Median Line and Primary Lower Band.
e. Strong Downtrend, when price is moving between Primary Lower Band and Secondary Lower Band.

Swing Targets

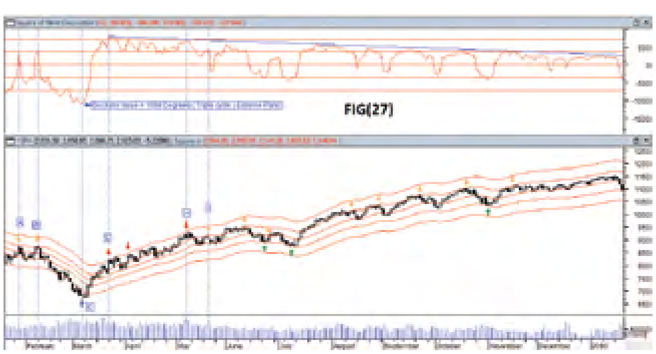
- In the case of sideways, Primary Upper band and Primary Lower Band are acting as a swing targets.
- In the case of Uptrend, Primary Upper Band and Median Line are acting as swing targets.
- In the case of Uptrend reaching Lower Band, it is considered a very good buying opportunity.
- In the case of Strong Uptrend, Secondary Upper Band and Primary Upper Band are acting as swing targets.
- In the case of Downtrend, Primary Lower Band and Median Line are acting as swing targets.
- In the case of Strong Downtrend, Secondary Lower Band and Primary Lower Band are acting as swing targets.
- In the case of Downtrend reaching the Primary Upper Band, it is considered a very good selling opportunity.
- Forecasting Change in Trend

When the price fails to reach any of the classified bands according to its current trend, we will expect that a trend may change to the next trend degree. As an example, if the current trend is sideways and the price failed to reach the Primary Upper Band, then trend reversal to a downtrend is expected.

Study of S&P 500 Index

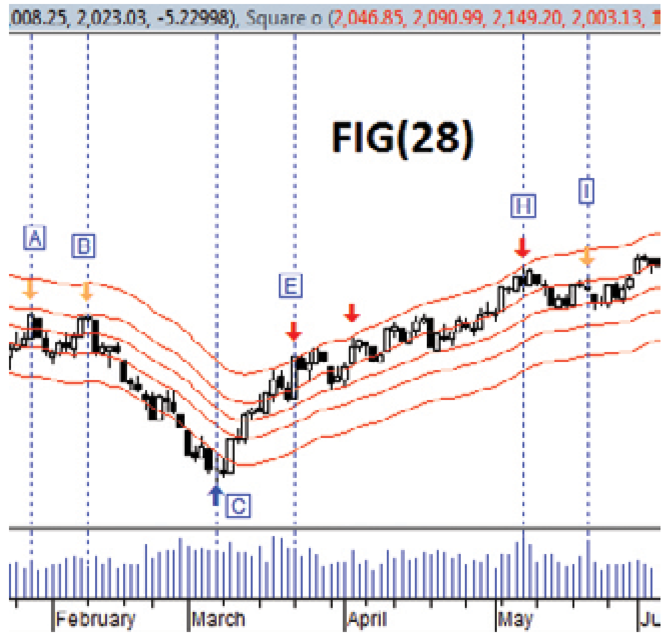
Figure 27 is a daily chart of S&P 500, from February 2009 to December 2009. Multiplier 10 is used with increment = 0.1 and angle rotation = 360

Figure 27. Daily Chart of S&P 500, February 2009 to December 2009



In the beginning of the chart, the index was moving in a downtrend; thus, reaching the Upper Primary Band at Points A and B was considered a very good selling opportunity.

Figure 28. Focus on Daily Chart of S&P 500



In Figure 28, Point C was out of the Lower Secondary Band, meaning that price rotates more than two complete cycles, and if we take a look at the oscillator, we will find that it reached 1080 degrees, or triple cycle, which means that prices must rebound very soon. Point E is allocated at Secondary Upper Band. It acted well as a resistance, which pushed prices to retrace testing its Upper Primary Band and then back again to the Upper Secondary Band, and then retraced to test the Median Line, but it failed to break it down. At this point, we must take into consideration that the market may reverse from downtrend to uptrend.

Study of Daily Chart of EASB.CA, a Security in the Egyptian Stock Exchange

Figure 29. EASB Daily Chart

By visual inspection in Figure 29, it can be found that the best matched values for angle rotation to equal = 120 and multiplier = 100

Notice how the Secondary Upper Band acted as a swing target and how the trend changed from normal uptrend to strong uptrend in the period that prices moved between Primary and Secondary Upper Band.

In Figure 30, the Square of Nine Oscillator has shown a reversal pattern from an extreme area, which was then reflected in the price action.

Figure 30. Square of Nine Oscillator Showing a Reversal Pattern

The same scenario happened in Figure 31 in a different period of time of the same security.

Figure 32 shows the harmonics between the price action and the Square of Nine Bands. Also, a clear divergence was shown by the oscillator, and a bullish single was triggered from the violation of the horizontal level, which shows that there is a potential trend reversal.

Figure 31. Same Scenario in Different Period of Time

Figure 32. Harmonics Between the Price Action and the Square of Nine Bands

Conclusion

Based on the work that was done by W.D. Gann, this paper has created a new theory that price movement is following a numerical rotation around pyramid cones, which is affected by specific angles. Every chart has its own nature that is translated by rotating around a specific angle, which could be repeated multiple times.

The analyst has to be careful, as he should select the best matched angle with the price chart movement.

The paper introduced two indicators that apply this theory: Square of Nine Bands and Square of Nine Oscillator. Those indicators have great merit in classifying the market trend and identifying its strength and finally providing specific targets for the market movement swings.

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W.D. Gann, Master Egg Course W.D. Gann, The Tunnel Thru The Air W.D. Gann, Truth of Stock Tape

Notes

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[2] Patrick Mikula, Gann's Scientific Methods Unveiled: Volume 1, p.139

[3] Patrick Mikula,Gann's Scientific Methods Unveiled: Volume 2, p.28

[4] W.D. Gann, The Tunnel Thru The Air, p.75

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[9] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.6

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[11] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.8

[12] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.10

[13] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.11

[14] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.28

[15] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.35

[16] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.56

[17] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.44

[18] Patrick Mikula, The Definitive Guide to Forecasting Using W.D. Gann's Square of Nine, p.54 Trading The Square Of Nine With a Calculator and Pencil, p.8

[19] To fine tune the results, the analyst may use any charting structure rather than Square of Nine except Circle of 24 (e.g., Octagon, Pentagon, Hexagon, Heptagon, Nonagon) to reach the best matches swing points, because Circle of 24 has a completely different calculation that is considered a stand-alone charting structure.

Software and Data

Market Warrior V 4.8

Gannzilla Pro V 5.6

Metastock V 11

Mubasher Pro

Yahoo Finance

The Calculation of the Target Levels of Japanese Candlestick Patterns by Using PatternsConfirmation Filters

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Abstract

This study aimed mainly to develop effective mathematical equations to determine the expected target levels of Japanese candlestick patterns, depending on patterns confirmation filters. To achieve the objectives of the study, a stratified random sample of 42 companies' shares were selected, based on the *Financial Times Global 500 Ranking Report* (FT 500, 2014). Afterwards, the cases were determined according to the conditions of the study, over a period of 11 years, including 111,469 trading days—from 31-08-2003 to 31-08-2014—where the number of cases in the first phase of was 7,481 cases, and in the second phase was 6,353 cases.

The study concluded that the most effective cases are the cases that contain 4 and 6 and 5 and 7 candles inside filters, respectively, where the percentage of success in accessing one of the target levels was 88.71%, with a profit rate ranging from +1.45% to +12.44%. On the other hand, the failure rate of accessing one of the target levels was 11.29%, with a loss rate ranging from -3.99% to -4.01%. The study also concluded that for the cases that contain 4 and 5 and 6 and 7 candles inside filters, generally the most effective mathematical equations to determine the expected target levels are 100% and 61.8% and 50%, respectively, where the rate of success in accessing one of these levels is equal to 62.32%, with the profit rate ranging from +5.10% to +12.44%. On the other hand, the failure rate in accessing one of these levels is equal to 37.69%, with loss rate ranging from -3.99% to -4.01%.

Keywords: Japanese candlesticks, Japanese candlestick patterns, confirmation filters, patterns confirmation filters, target levels.

Introduction

The Japanese candlestick charts achieved a large spread, and today have become the first choice among all of the financial market chart types due to the large benefits offered to traders. Despite this, there is a missing and incomplete part in Japanese candlesticks patterns, where these patterns do not have clear and agreed upon target levels.[1] Rather, the target levels are calculated based on different technical analysis tools, such as Support and Resistance, Trendlines, Chart Patterns, etc.[2]

Therefore, this study aimed mainly to complete the missing part in the Japanese candlestick patterns, which was to calculate the target levels by developing effective mathematical equations to determine the expected target levels depending on patterns confirmation filters, to identify the most effective cases when applying these equations, and to determine the most effective of these equations.

The Questions of the Study

The questions of this study are summarized as follows:

1. What is the rate of appearance of patterns confirmation filters based on the conditions of the study?
2. What is the percentage to access the target levels?
3. What is the percentage of the closing below or above the stop loss and failure to access one of the target levels?
4. What is the rate of the profits in the case of accessing the target levels?
5. What is the rate of the losses in the case of activating the stop loss?
6. What is the average time period to access the target levels?
7. What is the average time period to closing below or above the stop loss and failure to access one of the target levels?
8. What are the most effective mathematical equations and the most effective cases to calculate the target levels of Japanese candlesticks patterns by using patterns confirmation filters?

The Terminologies of the Study

The following is an explanation of the most important terminologies of this study.

Target Levels

The intended target levels in this study are levels that are calculated by special mathematical equations, which are five bullish targets (bullish target 100%, bullish target 61.8%, bullish target 50%, bullish target 38.2%, bullish target 23.6%) and five bearish targets (bearish target 100%, bearish target 61.8%, bearish target 50%, bearish target 38.2%, bearish target 23.6%).

The Japanese Candlestick Patterns

The intended Japanese candlestick patterns in this study include the following: all single, double, and complex Japanese candlestick patterns.

The Patterns Confirmation Filters

The intended patterns confirmation filters in this study include the following: the upper limit at the highest level in the Japanese candlestick pattern and the lower limit at the lowest level in a pattern. These filters are used to confirm the positive and negative Japanese candlestick patterns.

Clarification of the Calculation Method of the Target Levels of Japanese Candlestick Patterns by Using Patterns Confirmation Filters

The following is a detailed explanation of the method of this study for calculating the target levels of Japanese candlestick patterns.

The Positive Closing Above the Upper Filter

This closing is considered as confirmation for the positive Japanese candlestick patterns (or failure for the negative Japanese candlestick patterns), and you can use the following mathematical equations to calculate the targets of the positive closing above the upper filter based on the Fibonacci ratios (61.8%, 50%, 38.2%, and 23.6%) in addition to the 100% ratio:

- Bullish Target 100% = F2 + [(F1 - F2) × N]
- Bullish Target 61.8% = F2 + [(F1 - F2) × N × 0.618]
- Bullish Target 50% = F2 + [(F1 - F2) × N × 0.50]
- Bullish Target 38.2% = F2 + [(F1 - F2) × N × 0.382]
- Bullish Target 23.6% = F2 + [(F1 - F2) × N × 0.236]

Where:

F1: upper filter level.
F2: lower filter level.
N: Number of candles that closed between the upper filter level (F1) and the lower filter level (F2) of Japanese candlestick pattern.

Figures 1 through 5 show examples of how to calculate the bullish target levels.

Figure 1. An example of how to calculate the bullish target 100% of Takuri pattern (successful pattern)

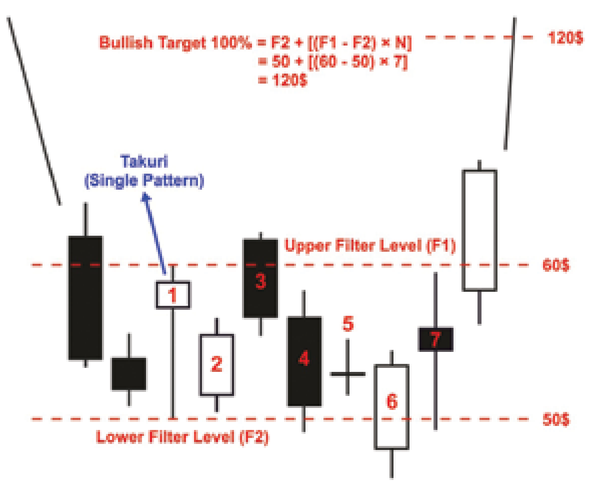

Figure 2. Siemens (SIEGn.DE) from 05-03-2009 to 01-10-2009: An example of how to calculate the bullish target 100% of thrusting pattern (successful pattern)

Figure 3. BT Group (BT.L) from 01-11-2010 to 16-05-2011: An Example of how to calculate the bullish target 61.8% of dark cloud cover pattern (failed pattern)

Figure 4. Anglo American (AAL.L) from 08-09-2010 to 29-12-2010: An example of how to calculate the bullish target 50% of upside Tasuki gap (successful pattern)

Figure 5. Roche (ROG.VX) from 15-01-2014 to 17-09-2014: An example of how to calculate the bullish target 38.2% of engulfing pattern (successful pattern)

The Negative Closing Below the Lower Filter

This closing is considered as confirmation for the negative Japanese candlestick patterns (or failure for the positive Japanese candlestick patterns), and you can use the following mathematical equations to calculate the targets of the negative closing below the lower filter based on the Fibonacci ratios (61.8%, 50%, 38.2%, and 23.6%) in addition to the 100% ratio:

- Bearish Target 100% = F1 - [(F1 - F2) × N]
- Bearish Target 61.8% = F1 - [(F1 - F2) × N × 0.618]
- Bearish Target 50% = F1 - [(F1 - F2) × N × 0.50]
- Bearish Target 38.2% = F1 - [(F1 - F2) × N × 0.382]
- Bearish Target 23.6% = F1 - [(F1 - F2) × N × 0.236]

Where:

F1: upper filter level.
F2: lower filter level.
N: Number of candles that closed between the upper filter level (F1) and the lower filter level (F2) of Japanese candlestick pattern.

Figures 6 through 10 show examples of how to calculate the bearish target levels.

Figure 6. An example of how to calculate the bearish target 100% of evening star pattern (successful pattern)

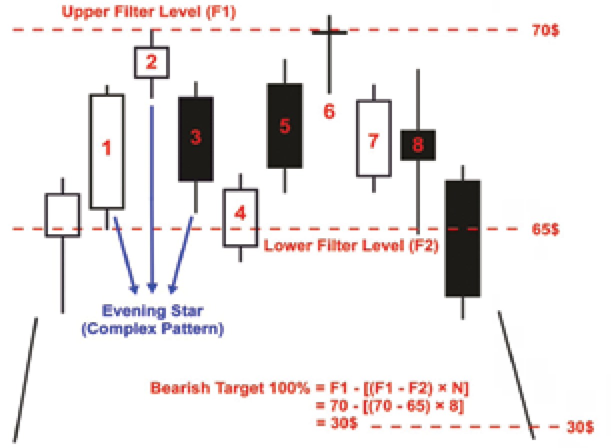

Figure 7. Sumitomo Mitsui Financial (8316.T) from 22-05-2008 to 23-10-2008: An example of how to calculate the bearish target 100% of descending Hawak pattern (successful pattern)

Figure 8. Lloyds Banking Group (LLOY.L) from 21-09-2009 to 21-12-2009: An example of how to calculate the bearish target 61.8% of homing pigeon pattern (failed pattern)

Figure 9. Apple (AAPL.OQ) from 19-11-2012 to 22-04-2013: An example of how to calculate the bearish target 50% of thrusting pattern (successful pattern)

Figure 10. General Electric (GE.N) from 18-12-2008 to 09-03-2009: An example of how to calculate the bearish target 38.2% of counterattack pattern (failed pattern)

The Methodology of the Study and the Method of Implementation of Statistics

The Financial Markets Where the Study Was Applied

To apply the study, a stratified random sample of 42 companies' shares were selected, based on the *Financial Times Global 500 Ranking Report* (FT 500 2014)[3] of the largest companies in the world, in terms of market capitalization. This report classified the largest companies in the world in six sections: Global, United States, Europe, United Kingdom, Japan, and Emerging Markets.

A stratified random sample of seven companies from each section were selected. The companies that were selected got ranked equal to the following Fibonacci sequence numbers: 1, 2, 3, 5, 8, 13, 21. In case of repetition of a company in more than one section, it was placed in the most appropriate section only. Select alternative companies got ranked equal to the following Fibonacci sequence numbers: 34, 55, 89, 144, 233, 377, respectively, until the number of companies selected from each section was equal to seven. Table 1 shows the companies' shares that have been selected.

Table 1. Companies' shares that were selected to apply to this study

No.	Company Name	Symbol (Reuters)	Country	Stock Exchange
Global:				
1	JP Morgan Chase	JPM.N	United States	New York
2	Industrial & Commercial Bank of China	601398.SS	China	Shanghai
3	Total	TOTF.PA	France	Paris
4	Commonwealth Bank of Australia	CBA.AX	Australia	Australia
5	Lloyds Banking Group	LLOY.L	United Kingdom	London
6	Medtronic	MDT.N	United States	New York
7	Jardine Matheson	JARD.SI	Hong Kong	Singapore
United States:				
8	Apple	AAPL.OQ	United States	NASDAQ
9	Exxon Mobil	XOM.N	United States	New York
10	Microsoft	MSFT.OQ	United States	NASDAQ
11	Berkshire Hathaway	BRKa.N	United States	New York
12	General Electric	GE.N	United States	New York
13	Pfizer	PFE.N	United States	New York
14	Amazon.com	AMZN.OQ	United States	NASDAQ
Europe:				
15	Roche	ROG.VX	Switzerland	SIX Swiss
16	Nestle	NESN.VX	Switzerland	SIX Swiss
17	Siemens	SIEGn.DE	Germany	Xetra
18	L'Oreal	OREP.PA	France	Paris
19	Rio Tinto	RIO.L	United Kingdom	London
20	Prudential	PRU.L	United Kingdom	London
21	Anglo American	AAL.L	United Kingdom	London
United Kingdom:				
22	Royal Dutch Shell	RDSa.L	United Kingdom	London
23	HSBC	HSBA.L	United Kingdom	London
24	BP	BP.L	United Kingdom	London
25	British American Tobacco	BATS.L	United Kingdom	London
26	AstraZeneca	AZN.L	United Kingdom	London
27	BHP Billiton	BLT.L	United Kingdom	London
28	BT Group	BT.L	United Kingdom	London
Japan:				
29	Toyota Motor	7203.T	Japan	Tokyo
30	Softbank	9984.T	Japan	Tokyo
31	Mitsubishi UFJ Financial	8306.T	Japan	Tokyo
32	Honda Motor	7267.T	Japan	Tokyo
33	Sumitomo Mitsui Financial	8316.T	Japan	Tokyo
34	Canon	7751.T	Japan	Tokyo
35	East Japan Railway	9020.T	Japan	Tokyo
Emerging Markets:				
36	PetroChina	601857.SS	China	Shanghai
37	China Construction Bank	601939.SS	China	Shanghai
38	Bank of China	601988.SS	China	Shanghai
39	Sinopec	600688.SS	China	Shanghai
40	Vale	VALE3.SA	Brazil	Sao Paolo
41	Lukoil	LKOH.MM	Russia	Moscow
42	Saudi Telecom	7010.SE	Saudi Arabia	Tadawul

The Period of Data Analysis

A period of 11 years was chosen to apply the study on the shares of the companies. This included 111,469 trading days during the period from 31-08-2003 to 31-08-2014 because this period reflects all phases of the financial markets—uptrends, downtrends, and sideways movements.

The Interval Used in the Analysis

The Japanese candles often reflect the psychological state of the traders during a short or intraday time period.[4] Therefore, the researcher focused on the daily interval in this study, where each candle in the charts and statistics used in this study represents one trading day.

The Source of the Data Used in the Analysis

We used the historical data service, "Data Link data" from Reuters, because Reuters is a specialized company and is reliable in providing the financial market data.

The Programs Used in the Analysis

- Metastock Version 10.1.
- Microsoft Office Excel 2013.

The Conditions of the Study

The following is a detailed presentation of the conditions in identifying the technical cases in this study.

The conditions in determining the uptrend and downtrend

The determination of the uptrend was at least achieved through two of the following conditions:

- Movement of 5-day exponential moving average above the 8- and 13-day exponential moving averages, with movement of the 8-day exponential moving average above the 13-day exponential moving average.
- The value of the positive Directional Index (+DI) for 13 days higher than the 20 level, and the indicator moves above the negative Directional Index (-DI).
- The value of the Average Directional Movement (ADX) for 13 days higher than the 20 level.
- Formation of at least five successive rising days.[5]

The determination of the downtrend was at least achieved through two of the following conditions:

- Movement of 5-day exponential moving average below the 8- and 13-day exponential moving averages, with movement of 8-day exponential moving average below 13-day exponential moving average.
- The value of the negative Directional Index (-DI) for 13 days higher than the 20 level, and the indicator moves above the positive Directional Index (+DI).
- The value of the Average Directional Movement (ADX) for 13 days higher than the 20 level.
- Formation of at least five successive failing days.[5]

The conditions of determining the successful deal

After closing above the upper filter (F1) of the Japanese candlestick pattern, the deal was considered successful when accessing the first bullish target level (bullish target 23.6%). But for the purposes of this study, and to make integrated and comprehensive statistics on the five bullish target levels, the deal will remain open until the highest target level (bullish target 100%) is accessed, or even closing below the level of the lower filter (F2).

On the other hand, after closing below the lower filter (F2) of the Japanese candlestick pattern, the deal was considered successful when accessing the first bearish target level (bearish target 23.6%). But for the purposes of this study, the deal will remain open until the lowest target level (bearish target 100%) is accessed, or even closing above the level of the upper filter (F1).

The conditions of determining the failed deal

After closing above the upper filter (F1) of the Japanese candlestick pattern, the deal is considered a failed deal in the case of closing below the lower filter (F2) of the pattern (stop loss level) before accessing the nearest bullish target level (bullish target 23.6%). On the other hand, after closing below the lower filter (F2) of the pattern, the deal is considered a failed deal in the case of closing above the upper filter (F1) of the pattern (stop loss level) before accessing the nearest bearish target level (bearish target 23.6%).

The conditions of determining the patterns confirmation filters to calculate the target levels in this study

This study focuses on the confirmation of the filter patterns that contain 4 to 10 candles only, including a candle (or candles) of Japanese candlestick patterns. However, this method can be applied to any number of candles inside the filters.

After determining the uptrend and downtrend on the basis of the conditions of this study, we determined the upper and lower filters on the first pattern that appears of Japanese candlestick patterns, and focused on this pattern until closing above the upper filter or below the lower filter. Intraday breakout is not taken into account, whether by shadows or by the open. The focus is only on close above the upper filter or below the lower filter. After that, target levels were calculated, as explained in this study and according to the specified conditions.

The first step in determining the upper and lower filter will be on the first candle that represents one of the single Japanese candlestick patterns, and if the candle that appears directly after the first candle completes a double pattern, in this case the focus is on determining the upper and lower filter on the double pattern. And if the candle that appears directly after the first two candles directly completes a complex pattern, in this case the focus is on determining the upper and lower filter on the complex pattern, and so on, on the condition that such candles successively will jointly make one of the Japanese candlestick patterns.

Results

General Results for All Cases of the Study

Table 2 shows that the success rate in accessing one of the target levels was 85.68%, with a profit rate ranging from +2.04% to +13.99%, and the rate of the time period to access one of the target levels ranged from 3 to 45 trading days. On the other hand, the failure rate to access one of the target levels was 14.32%, with loss rate ranging from -4.04% to -4.07%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to 9 trading days.

Table 2. Statistics for all cases of the study

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratio of the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Depending on Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days) [Std. Dev.]	
23.6%	Bullish	500	1109	6.68%	14.82%	+2.04% [1.95]	+2.16% [2.57]	0.49 [0.46]	0.52 [0.63]	3.18 [6.15]	3.47 [6.68]
	Bearish	609		8.14%		+2.27% [2.98]		0.55 [0.73]		3.71 [7.08]	
38.2%	Bullish	418	951	5.59%	12.71%	+4.03% [4.11]	+4.16% [4.42]	0.99 [0.93]	1.02 [1.05]	8.51 [18.50]	8.09 [17.36]
	Bearish	533		7.12%		+4.26% [4.65]		1.05 [1.13]		7.76 [16.40]	
50%	Bullish	350	724	4.68%	9.68%	+5.69% [4.65]	+5.86% [5.66]	1.43 [1.13]	1.46 [1.38]	12.31 [19.66]	13.15 [25.05]
	Bearish	374		5.00%		+6.02% [6.46]		1.49 [1.58]		13.94 [29.17]	
61.8%	Bullish	586	1255	7.83%	16.78%	+7.67% [9.41]	+7.67% [8.50]	1.93 [2.26]	1.92 [2.05]	22.61 [66.54]	20.14 [56.44]
	Bearish	669		8.94%		+7.67% [7.61]		1.90 [1.86]		17.97 [45.69]	
100%	Bullish	1491	2371	19.93%	31.69%	+13.99% [12.75]	+13.22% [11.81]	3.53 [3.10]	3.32 [2.88]	45.44 [83.18]	42.38 [80.74]
	Bearish	880		11.76%		+11.91% [9.89]		2.98 [2.42]		37.21 [76.15]	
Failed Deals	Bullish	495	1071	6.62%	14.32%	-4.07% [3.19]	-4.05% [2.99]	1.00 [0.76]	1.00 [0.73]	8.97 [13.90]	9.11 [13.92]
	Bearish	576		7.70%		-4.04% [2.80]		1.00 [0.69]		9.23 [13.93]	
Summary		7481 (Total)		100% (Total)		+8.05%* [9.60]		2.01* [2.35]		22.91* [58.38]	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Results for the Cases That Contain Four Candles Inside Filters

Table 3 shows that the success rate in accessing one of the target levels was 86.18%, with a profit rate ranging from +2% to +9.46%, and the rate of the time period to access the target levels ranged from 2 to 23 trading days. On the other hand, the failure rate to access one of target levels was 13.82%, with loss rate ranging from -3.82% to -3.87%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels approximately equal to 7 trading days.

Table 3. Statistics for the cases that contain four candles inside filters

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratio of the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Depending on Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days) [Std. Dev.]	
23.6%	Bullish	0	0	0.00%	0.00%	0.00% [0]	0.00% [0]	0.00 [0]	0.00 [0]	0.00 [0]	0.00 [0]
	Bearish	0		0.00%		0.00% [0]		0.00 [0]		0.00 [0]	
38.2%	Bullish	153	353	5.63%	12.98%	+2.00% [1.40]	+2.24% [1.72]	0.52 [0.36]	0.58 [0.45]	2.13 [2.57]	2.68 [4.36]
	Bearish	200		7.35%		+2.42% [1.91]		0.63 [0.50]		3.11 [5.30]	
50%	Bullish	145	301	5.33%	11.07%	+3.40% [2.48]	+3.32% [2.25]	0.88 [0.64]	0.86 [0.58]	4.68 [7.29]	4.61 [6.75]
	Bearish	156		5.74%		+3.25% [2.01]		0.85 [0.53]		4.56 [6.20]	
61.8%	Bullish	262	571	9.63%	20.99%	+4.82% [3.60]	+4.67% [3.24]	1.24 [0.93]	1.21 [0.84]	9.53 [14.23]	8.21 [12.26]
	Bearish	309		11.36%		+4.54% [2.90]		1.19 [0.76]		7.09 [10.16]	
100%	Bullish	662	1119	24.34%	41.14%	+9.46% [7.17]	+9.17% [6.87]	2.44 [1.85]	2.38 [1.78]	22.56 [39.24]	20.52 [37.73]
	Bearish	457		16.80%		+8.74% [6.38]		2.29 [1.67]		17.56 [35.23]	
Failed Deals	Bullish	190	376	6.99%	13.82%	-3.87% [2.99]	-3.85% [2.90]	1.00 [0.77]	1.00 [0.75]	6.87 [14.28]	6.74 [11.40]
	Bearish	186		6.84%		-3.82% [2.80]		1.00 [0.73]		6.61 [7.36]	
Summary		2720 (Total)		100% (Total)		+6.28%* [5.86]		1.63* [1.52]		12.79* [27.98]	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Results for the Cases That Contain Five Candles Inside Filters

Table 4 shows that the success rate in accessing one of the target levels was 95.04%, with a profit rate ranging from +0.71% to +12.66%, and the rate of the time period to access the target levels ranged from 1 to 41 trading days. On the other hand, the failure rate to access one of the target levels was 4.96%, with a loss rate ranging from -3.50% to -4.03%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to five trading days.

Table 4. Statistics for the cases that contain five candles inside filters

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratio of the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Dependingon Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days) [Std. Dev.]	
23.6%	Bullish	166	358	9.36%	20.18%	+0.71% [0.86]	+0.73% [0.79]	0.20 [0.25]	0.19 [0.21]	1.34 [2.05]	1.32 [1.79]
	Bearish	192		10.82%		+0.75% [0.74]		0.19 [0.18]		1.30 [1.53]	
38.2%	Bullish	109	259	6.14%	14.60%	+2.93% [1.85]	+3.46% [2.73]	0.84 [0.53]	0.90 [0.69]	4.61 [6.72]	5.40 [13.65]
	Bearish	150		8.46%		+3.84% [3.17]		0.95 [0.79]		5.97 [16.97]	
50%	Bullish	89	190	5.02%	10.71%	+5.36% [3.24]	+5.18% [3.51]	1.53 [0.93]	1.38 [0.94]	8.78 [12.35]	8.52 [11.01]
	Bearish	101		5.69%		+5.03% [3.73]		1.25 [0.93]		8.29 [9.66]	
61.8%	Bullish	141	306	7.95%	17.25%	+6.64% [3.64]	+7.17% [5.57]	1.90 [1.04]	1.89 [1.42]	15.96 [21.41]	14.13 [18.69]
	Bearish	165		9.30%		+7.62% [6.76]		1.89 [1.68]		12.57 [15.84]	
100%	Bullish	360	573	20.29%	32.30%	+12.66% [10.16]	+12.26% [9.59]	3.62 [2.91]	3.34 [2.66]	40.50 [67.18]	38.50 [67.85]
	Bearish	213		12.01%		+11.59% [8.49]		2.87 [2.11]		35.14 [68.83]	
Failed Deals	Bullish	36	88	2.03%	4.96%	-3.50% [2.45]	-3.81% [2.60]	1.00 [0.70]	1.00 [0.68]	3.64 [3.03]	4.53 [4.60]
	Bearish	52		2.93%		-4.03% [2.68]		1.00 [0.67]		5.15 [5.34]	
Summary		1774 (Total)		100% (Total)		+6.74%* [7.71]		1.82* [2.11]		17.72* [43.70]	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Results for the Cases That Contain Six Candles Inside Filters

Table 5 shows that the success rate in accessing one of the target levels was 88.04%, with a profit rate ranging from +1.69% to +17.22%, and the rate of the time period to access the target levels ranged from 2 to 61 trading days. On the other hand, the failure rate to access one of the target levels was 11.96%, with a loss rate ranging from -4.06% to -4.07%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to 7 trading days.

Table 5. Statistics for the cases that contain six candles inside filters

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratio of the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Depending on Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days) [Std. Dev.]	
23.6%	Bullish	129	301	11.43%	26.66%	+1.78% [1.44]	+1.73% [1.49]	0.44 [0.36]	0.42 [0.37]	2.20 [3.43]	2.45 [4.06]
	Bearish	172		15.23%		+1.69% [1.53]		0.41 [0.37]		2.63 [4.46]	
38.2%	Bullish	57	134	5.05%	11.87%	+4.00% [2.40]	+4.23% [2.93]	0.98 [0.59]	1.04 [0.72]	10.68 [19.18]	8.56 [14.36]
	Bearish	77		6.82%		+4.41% [3.26]		1.08 [0.80]		6.99 [9.00]	
50%	Bullish	47	103	4.16%	9.12%	+7.65% [5.16]	+7.84% [6.28]	1.88 [1.27]	1.93 [1.54]	20.81 [22.66]	17.09 [27.94]
	Bearish	56		4.96%		+8.00% [7.08]		1.96 [1.74]		13.96 [31.36]	
61.8%	Bullish	81	167	7.17%	14.79%	+8.31% [4.96]	+9.28% [7.49]	2.05 [1.22]	2.28 [1.84]	22.57 [24.08]	24.03 [49.32]
	Bearish	86		7.62%		+10.20% [9.17]		2.50 [2.25]		25.41 [64.61]	
100%	Bullish	196	289	17.36%	25.60%	+17.22% [15.09]	+16.61% [13.82]	4.24 [3.72]	4.09 [3.40]	60.78 [123.89]	57.29 [111.87]
	Bearish	93		8.24%		+15.31% [10.54]		3.76 [2.59]		49.95 [80.39]	
Failed Deals	Bullish	63	135	5.58%	11.96%	-4.06% [2.23]	-4.07% [2.98]	1.00 [0.55]	1.00 [0.73]	6.14 [6.33]	6.53 [7.11]
	Bearish	72		6.38%		-4.07% [3.51]		1.00 [0.86]		6.88 [7.71]	
Summary		1129 (Total)		100% (Total)		+8.29% [10.32] *		2.04 [2.54] *		24.36 [68.27] *	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Results for the Cases That Contain Seven Candles Inside Filters

Table 6 shows that the success rate in accessing one of the target levels was 83.84%, with a profit rate ranging from +2.44% to +20.55%, and the rate of the time period to access the target levels ranged from 4 to 80 trading days. On the other hand, the failure rate to access one of the target levels was 16.16%, with a loss rate ranging from -4.40% to -4.79%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to nine trading days.

Table 6. Statistics for the cases that contain seven candles inside filters

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratioof the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Depending on Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days) [Std. Dev.]	
23.6%	Bullish	81	182	11.10%	24.93%	+2.44% [1.35]	+2.66% [1.88]	0.51 [0.28]	0.58 [0.42]	3.52 [5.19]	3.77 [7.69]
	Bearish	101		13.84%		+2.83% [2.21]		0.64 [0.50]		3.97 [9.21]	
38.2%	Bullish	44	90	6.03%	12.33%	+7.09% [3.97]	+6.73% [4.49]	1.48 [0.83]	1.47 [0.99]	19.75 [26.54]	18.84 [28.00]
	Bearish	46		6.30%		+6.40% [4.92]		1.45 [1.12]		17.98 [29.31]	
50%	Bullish	36	64	4.93%	8.77%	+8.00% [3.56]	+9.30% [5.64]	1.67 [0.74]	2.03 [1.28]	19.28 [20.00]	27.59 [32.93]
	Bearish	28		3.84%		+10.96% [7.18]		2.49 [1.63]		38.29 [41.96]	
61.8%	Bullish	45	94	6.16%	12.88%	+10.93% [7.35]	+11.38% [7.46]	2.28 [1.53]	2.49 [1.64]	33.04 [41.46]	29.65 [36.89]
	Bearish	49		6.71%		+11.79% [7.54]		2.68 [1.71]		26.53 [31.81]	
100%	Bullish	119	182	16.30%	24.93%	+20.55% [16.08]	+19.29% [14.22]	4.29 [3.36]	4.13 [2.99]	79.74 [87.62]	71.05 [79.13]
	Bearish	63		8.63%		+16.92% [9.34]		3.84 [2.12]		54.65 [56.37]	
Failed Deals	Bullish	44	118	6.03%	16.16%	-4.79% [4.69]	-4.55% [3.65]	1.00 [0.98]	1.00 [0.79]	8.98 [11.32]	8.81 [10.95]
	Bearish	74		10.14%		-4.40% [2.84]		1.00 [0.64]		8.70 [10.73]	
Summary		730 (Total)		100% (Total)		+10.24% [10.94] *		2.21 [2.33] *		32.46 [55.10] *	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Results for the Cases That Contain Eight Candles Inside Filters

Table 7 shows that the success rate in accessing one of the target levels was 70.75%, with a profit rate ranging from +3.12% to +26.85%, and the rate of the time period to access the target levels ranged from 5 to 178 trading days. On the other hand, the failure rate to access one of the target levels was 29.25%, with a loss rate ranging from -3.98% to -4.47%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to 12 trading days.

Table 7. Statistics for the cases that contain eight candles inside filters

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratio of the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Depending on Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days) [Std. Dev.]	
23.6%	Bullish	62	133	11.70%	25.09%	+3.12% [2.05]	+3.60% [4.32]	0.70 [0.46]	0.87 [1.08]	4.95 [8.34]	6.01 [9.06]
	Bearish	71		13.40%		+4.02% [5.56]		1.01 [1.40]		6.93 [9.55]	
38.2%	Bullish	25	55	4.72%	10.38%	+10.75% [9.02]	+9.08% [7.11]	2.40 [2.02]	2.15 [1.62]	15.24 [9.98]	17.27 [15.91]
	Bearish	30		5.66%		+7.70% [4.55]		1.94 [1.14]		18.97 [19.35]	
50%	Bullish	19	29	3.58%	5.47%	+9.14% [2.99]	+9.70% [4.49]	2.04 [0.67]	2.27 [1.12]	29.95 [25.01]	32.59 [37.77]
	Bearish	10		1.89%		+10.77% [6.29]		2.71 [1.58]		37.60 [53.95]	
61.8%	Bullish	24	57	4.53%	10.75%	+17.35% [14.14]	+16.72% [12.38]	3.88 [3.16]	4.00 [2.93]	77.08 [105.84]	71.09 [102.08]
	Bearish	33		6.23%		+16.26% [10.89]		4.09 [2.74]		66.73 [99.03]	
100%	Bullish	74	101	13.96%	19.06%	+24.07% [15.47]	+24.81% [16.53]	5.38 [3.46]	5.75 [3.90]	92.20 [141.48]	115.14 [165.80]
	Bearish	27		5.09%		+26.85% [18.98]		6.75 [4.77]		178 [206.33]	
Failed Deals	Bullish	66	155	12.45%	29.25%	-4.47% [4.01]	-4.19% [3.23]	1.00 [0.90]	1.00 [0.75]	13.26 [16.24]	12.07 [13.42]
	Bearish	89		16.79%		-3.98% [2.49]		1.00 [0.63]		11.19 [10.77]	
Summary		530 (Total)		100% (Total)		+12.59% [13.65] *		2.95 [3.20] *		49.00 [106.02] *	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Results for the Cases That Contain Nine Candles Inside Filters

Table 8 shows that the success rate in accessing one of the target levels was 70.46%, with a profit rate ranging from +3.99% to +29.92%, and the rate of the time period to access the target levels ranged from 7 to 150 trading days. On the other hand, the failure rate to access one of the target levels was 29.55%, with a loss rate ranging from -4.11% to -4.43%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to 11 trading days.

Table 8. Statistics for the cases that contain nine candles inside filters

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratio of the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Depending on Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days)[Std. Dev.]	
23.6%	Bullish	38	80	10.80%	22.73%	+3.99% [1.74]	+4.19% [2.43]	0.97 [0.42]	0.98 [0.56]	9.97 [13.79]	8.19 [10.89]
	Bearish	42		11.93%		+4.37% [2.90]		0.99 [0.66]		6.57 [6.96]	
38.2%	Bullish	21	42	5.97%	11.93%	+7.81% [3.51]	+8.66% [6.68]	1.90 [0.85]	2.02 [1.52]	28.71 [49.64]	23.14 [37.92]
	Bearish	21		5.97%		+9.50% [8.69]		2.15 [1.96]		17.57 [18.69]	
50%	Bullish	7	21	1.99%	5.97%	+15.02% [13.55]	+12.26% [8.58]	3.65 [3.29]	2.86 [2.09]	40.43 [45.71]	44.05 [45.87]
	Bearish	14		3.98%		+10.88% [3.59]		2.46 [0.81]		45.86 [45.84]	
61.8%	Bullish	25	43	7.10%	12.22%	+20.29% [29.28]	+18.16% [23.51]	4.93 [7.12]	4.31 [5.70]	68.80 [82.11]	57.26 [67.83]
	Bearish	18		5.11%		+15.19% [10.72]		3.43 [2.42]		41.22 [34.42]	
100%	Bullish	44	62	12.50%	17.61%	+29.92% [18.04]	+29.52% [16.97]	7.27 [4.39]	7.04 [4.08]	120.16 [84.31]	128.74 [97.93]
	Bearish	18		5.11%		+28.57% [13.98]		6.45 [3.16]		149.72 [122.64]	
Failed Deals	Bullish	48	104	13.64%	29.55%	-4.11% [3.15]	-4.28% [2.94]	1.00 [0.77]	1.00 [0.69]	9.75 [5.89]	11.07 [10.12]
	Bearish	56		15.91%		-4.43% [2.74]		1.00 [0.62]		12.20 [12.56]	
Summary		352 (Total)		100% (Total)		+14.38%* [16.82]		3.41* [4.04]		52.40* [76.80]	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Results for the Cases That Contain 10 Candles Inside Filters

Table 9 shows that the success rate in accessing one of the target levels was 61.38%, with a profit rate ranging from +5.43% to +32.07%, and the rate of the time period to access the target levels ranged from 5 to 182 trading days. On the other hand, the failure rate to access one of the target levels was 38.62%, with a loss rate ranging from -3.93% to -4.02%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to 20 trading days.

Table 9. Statistics for the cases that contain 10 candles inside filters

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratio of the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Depending on Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days) [Std. Dev.]	
23.6%	Bullish	24	55	9.76%	22.36%	+5.43% [2.74]	+5.85% [3.40]	1.35 [0.68]	1.47 [0.86]	4.63 [3.55]	9.04 [10.43]
	Bearish	31		12.60%		+6.17% [3.80]		1.57 [0.97]		12.45 [12.51]	
38.2%	Bullish	9	18	3.66%	7.32%	+9.70% [4.48]	+12.97% [11.47]	2.41 [1.11]	3.27 [2.92]	29.67 [19.69]	32.33 [25.45]
	Bearish	9		3.66%		+16.24% [14.89]		4.13 [3.79]		35.00 [29.89]	
50%	Bullish	7	16	2.85%	6.50%	+13.50% [4.82]	+19.62% [14.96]	3.36 [1.20]	4.96 [3.81]	46.43 [45.83]	69.88 [60.53]
	Bearish	9		3.66%		+24.37% [18.11]		6.20 [4.61]		88.11 [64.19]	
61.8%	Bullish	8	17	3.25%	6.91%	+26.27% [22.99]	+24.44% [20.28]	6.53 [5.72]	6.15 [5.08]	202.25 [429.57]	173.41 [322.58]
	Bearish	9		3.66%		+22.82% [17.36]		5.80 [4.42]		147.78 [176.45]	
100%	Bullish	36	45	14.63%	18.29%	+31.38% [18.88]	+31.52% [17.56]	7.80 [4.69]	7.87 [4.37]	131.28 [143.52]	141.49 [141.55]
	Bearish	9		3.66%		+32.07% [10.72]		8.16 [2.73]		182.33 [125.29]	
Failed Deals	Bullish	48	95	19.51%	38.62%	-4.02% [2.31]	-3.98% [2.19]	1.00 [0.57]	1.00 [0.55]	18.27 [21.18]	19.78 [28.98]
	Bearish	47		19.11%		-3.93% [2.07]		1.00 [0.53]		21.32 [35.14]	
Summary		246 (Total)		100% (Total)		+17.90%* [17.26]		4.49* [4.32]		76.24* [149.67]	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Discussion

The goal was to achieve the objectives of the study, to reach clear and comprehensive answers to the questions of the study, and to analyze the results perfectly and precisely. The results of the study were analyzed and its questions were answered in two phases. The first phase included all cases of the study. The second phase included the effective cases only, excluding the ineffective cases, and the cases that appeared rarely.

The First Phase Included All Cases of the Study

The answer to questions of the study using all cases of the study (Table 2):

1. What is the rate of appearance of patterns confirmation filters based on the conditions of the study? The appearance frequency of the patterns confirmation filters was 7,481 cases during the study period, which was conducted on 42 shares, through the analysis of 111,469 trading days over 11 years. This means that the frequency of the patterns confirmation filters appeared at the rate of once every 15 trading days, depending on the conditions of this study.
2. What is the percentage to access the target levels? The total percentage of accessing one of target levels is equal to 85.68%.
3. What is the percentage of the closing below or above the stop loss and failure to access one of the target levels? The total percentage of the failure to access the target levels is equal to 14.32%.

4. What is the rate of the profits in the case of accessing the target levels? The overall rate of profits for the cases that have accessed the target levels is equal to 8.05%.
5. What is the rate of the losses in the case of activating the stop loss? The overall rate of losses for the cases that failed to access the target levels is equal to -4.05%.
6. What is the average time period to access the target levels? The overall average of the time period to access the target levels is approximately equal to 23 trading days.
7. What is the average of time period to closing below or above the stop loss and failure to access one of the target levels? The overall average of the time period to closing below or above the stop loss and failure of accessing the target levels is approximately equal to nine trading days.
8. What are the most effective mathematical equations and the most effective cases to calculate the target levels of Japanese candlestick patterns by using patterns confirmation filters? By comparing the rate of risk/reward ratio, as in Table 2, it shows that the 23.6% target level achieved a profit rate less than the loss rate! Therefore, this equation is considered ineffective. When it excluded the target level of 23.6%, the overall rate of success in accessing the target levels of 100% and 61.8% and 50% and 38.6% is equal to 70.86%, and the failure rate is equal to 29.14%.

Table 3 shows that the frequency of the cases that contain four candles inside filters was 2,720 cases, which is equivalent to the rate of 36.36% of the total cases of the study. Further, the table shows the target levels of 23.6% and 38.2% and 50% achieved a profit rate less than the loss rate! Therefore, these equations are considered ineffective. When excluding the target levels of 23.6% and 38.2% and 50%, the overall rate of success in accessing the target levels of 100% and 61.8% is equal to 62.13%, and the failure rate is equal to 37.87%.

Table 4 shows that the frequency of the cases that contain five candles inside filters was 1,774 cases, which is equivalent to the rate of 23.71% of the total cases of the study. Further, the table shows the target levels of 23.6% and 38.2% achieved a profit rate less than loss rate! Therefore, these equations are considered ineffective. When excluding the target levels of 23.6% and 38.2%, the overall rate of success in accessing the target levels of 100% and 61.8% and 50% is equal to 60.26%, and the failure rate is equal to 39.74%.

Table 5 shows that the frequency of the cases that contain six candles inside filters was 1,129 cases, which is equivalent to the rate of 15.09% of the total cases of the study. Further, the table shows the target level of 23.6% achieved a profit rate less than loss rate! Therefore, this equation is considered ineffective. When excluding the target level of 23.6%, the overall rate of success in accessing the target levels of 100% and 61.8% and 50% and 38.2% is equal to 61.38%, and the failure rate is equal to 38.62%.

Table 6 shows that the frequency of the cases that contain seven candles inside filters was 730 cases, which is equivalent to the rate of 9.76% of the total cases of the study. Further, the table shows the target level of 23.6% achieved a profit rate less than loss rate! Therefore, this equation is considered ineffective. When excluding the target level of 23.6%, the overall rate of success in accessing the target levels of 100% and 61.8% and 50% and 38.2% is equal to 58.91%, and the failure rate is equal to 41.09%.

Table 7 shows that the frequency of the cases that contain eight candles inside filters was 530 cases, which is equivalent to the rate of 7.08% of the total cases of the study. Further, the table shows the target level of 23.6% achieved a profit rate less than loss rate! Therefore, this equation is considered ineffective. When excluding the target level of 23.6%, the overall rate of success in accessing the target levels of 100% and 61.8% and 50% and 38.2% is equal to 45.66%, and the failure rate is equal to 54.34%.

Table 8 shows that the frequency of the cases that contain nine candles inside filters was 352 cases, which is equivalent to the rate of 4.71% of the total cases of the study. Further, the table shows the target level of 23.6% achieved a profit rate less than loss rate! Therefore, this equation is considered ineffective. When excluding the target level of 23.6%, the overall rate of success in accessing the target levels of 100% and 61.8% and 50% and 38.2% is equal to 47.73%, and the failure rate is equal to 52.28%.

Table 9 shows that the frequency of the cases that contain 10 candles inside filters was 246 cases, which is equivalent to the rate of 3.29% of the total cases of the study. Further, the table shows that the overall rate of success in accessing to the target levels of 100% and 61.8% and 50% and 38.2% and 23.6% is equal to 61.38%, with the profit rate ranging from +5.43% to +32.07%. On the other hand, the failure rate to access one of these levels is equal to 38.62%, with loss rate ranging from -3.93% to -4.02%.

Based on the above discussion of the results, and after excluding the target level of 23.6%, it is clear that the order of the most effective cases based on the number of candles inside filters, in terms of success rate to access one of the target levels, is as follows:

1. Cases that contain four candles inside filters: where the success rate to access one of target levels was 62.13%.
2. Cases that contain six candles inside filters: where the success rate to access one of target levels was 61.38%.
3. Cases that contain 10 candles inside filters: where the success rate to access one of target levels was 61.38%.
4. Cases that contain five candles inside filters: where the success rate to access one of target levels was 60.26%.
5. Cases that contain seven candles inside filters: where the success rate to access one of target levels was 58.91%.

Based on the above discussion of the results and as shown in Table 2, after excluding the target level of 23.6%, it is clear that the order of the most effective mathematical equations based on the overall rate of access to the target levels of 100% and 61.8 and 50% and 38.2% is as follows:

1. The target level of 100%: where the total ratio to access this target level was 31.69%, with an average profit of +13.22%.
2. The target level of 61.8%: where the total ratio to access this target level was 16.78%, with an average profit of +7.67%.
3. The target level of 38.2%: where the total ratio to access this target level was 12.71%, with an average profit of +4.16%.

4. The target level of 50%: where the total ratio to access this target level was 9.68%, with an average profit of +5.86%.

The Second Phase: Including the Effective Cases Only, Excluding the Ineffective Cases and the Cases That Appeared Rarely

Tables 2 through 9 show that the frequency of the cases that contain between 4 and 7 candles inside filters was 6,353 cases, which is equivalent to the rate of 84.92% of the total cases of the study. On the other hand, the appearance frequency of the cases that contain between 8 and 10 candles inside filters was 1,128 cases, which is equivalent to the rate of 15.08% of the total cases of the study.

Based on the above discussion of the results in the first phase, it is clear that the cases that contain 8 and 9 candles inside filters are ineffective, and the frequency of these cases was only 882 cases, which is equivalent to the rate of 11.79% of the total cases of the study. In addition to this, the cases that contain 10 candles inside filters appeared in only 3.29% of the total cases of the study.

Because the cases that contain between 8 and 10 candles inside filters were generally considered ineffective and appeared in only 15.08% of the total cases of the study, these cases will be excluded from the second phase, and the focus will be only on the cases that contain between 4 and 7 candles inside filters, as shown in Table 10.

Table 10. Statistics for the cases that contain 4—7 candles inside filters

Target Levels		Number of Deals		The Deals Ratio (%) (of Total)		Average of Profit/Loss Ratio of the Deals (%) [Std. Dev.]		Risk/Reward Ratio (Depending on Failed Deals) [Std. Dev.]		Average of Duration of Deals (Days) [Std. Dev.]	
23.6%	Bullish	465	841	7.32%	13.24%	+1.45% [1.39]	+1.50% [1.55]	0.35 [0.32]	0.36 [0.36]	2.11 [3.52]	2.25 [4.57]
	Bearish	376		5.92%		+1.55% [1.66]		0.37 [0.39]		2.37 [5.27]	
38.2%	Bullish	363	836	5.71%	13.16%	+3.21% [2.69]	+3.42% [3.00]	0.80 [0.61]	0.85 [0.71]	6.35 [13.88]	6.21 [14.38]
	Bearish	473		7.45%		+3.58% [3.21]		0.89 [0.77]		6.09 [14.75]	
50%	Bullish	317	658	4.99%	10.36%	+5.10% [3.80]	+5.15% [4.41]	1.30 [0.95]	1.29 [1.07]	9.88 [15.14]	9.93 [18.31]
	Bearish	341		5.37%		+5.19% [4.92]		1.29 [1.17]		9.98 [20.83]	
61.8%	Bullish	529	1138	8.33%	17.91%	+6.36% [4.68]	+6.57% [5.60]	1.63 [1.14]	1.66 [1.36]	15.24 [22.56]	13.90 [26.28]
	Bearish	609		9.59%		+6.76% [6.28]		1.68 [1.52]		12.73 [29.07]	
100%	Bullish	1337	2163	21.05%	34.05%	+12.44% [11.10]	+11.83% [10.14]	3.19 [2.76]	3.01 [2.51]	38.08 [72.54]	34.45 [66.65]
	Bearish	826		13.00%		+10.84% [8.24]		2.72 [2.03]		28.57 [55.31]	
Failed Deals	Bullish	333	717	5.24%	11.29%	-3.99% [3.12]	-4.00% [3.03]	1.00 [0.76]	1.00 [0.75]	6.66 [11.98]	6.77 [10.06]
	Bearish	384		6.04%		-4.01% [2.95]		1.00 [0.73]		6.87 [8.03]	
Summary		6353 (Total)		100% (Total)		+7.20%* [8.09]		1.82* [2.02]		18.44* [45.71]	

* The average of the target levels of 23.6%, 38.2%, 50%, 61.8%, 100% only, without the failed deals.

Table 10 shows that the success rate in accessing one of the target levels was 88.71%, with a profit rate ranging from +1.45% to +12.44%, and the rate of the time period to access the target levels ranged from 2 to 38 trading days. On the other hand, the failure rate to access one of the target levels was 11.29%, with loss rate ranging from -3.99% to -4.01%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to 7 trading days.

The answer to questions of the study by using the cases that contain between 4 and 7 candles inside filters (Table 10):

1. What is the rate of appearance of patterns confirmation filters based on the conditions of the study? The frequency of the patterns confirmation filters was 6,353 cases during the study period, which was conducted on 42 shares through the analysis of 111,469 trading days over 11 years. This means that the frequency of the patterns confirmation filters appeared at the rate of once every 18 trading days, depending on the conditions of this study.
2. What is the percentage to access the target levels? The total percentage of accessing one of target levels is equal to 88.71%.
3. What is the percentage of the closing below or above the stop loss and failure to access one of the target levels? The total percentage of the failure to access the target levels is equal to 11.29%.
4. What is the rate of the profits in the case of accessing to the target levels? The overall rate of profits for the cases that have accessed the target levels is equal to 7.20%.
5. What is the rate of the losses in the case of activating the stop loss? The overall rate of losses for the cases that failed to access the target levels is equal to -4%.
6. What is the average time period to access the target levels? The overall average of the time period to access the target levels is approximately equal to 18 trading days.
7. What is the average of time period to closing below or above the stop loss and failure to access one of the target levels? The overall average of the time period to closing below or above the stop loss and failure of accessing to the target levels approximately equal to 7 trading days.
8. What are the most effective mathematical equations and the most effective cases to calculate the target levels of Japanese candlestick patterns by using patterns confirmation filters? Comparing the rate of Risk/Reward Ratio, as in Table 10, shows that the target levels of 23.6% and 38.2% achieved a profit rate less than the loss rate! Therefore, these equations are considered ineffective. When excluding the target levels of 23.6% and 38.2%, the overall rate of success in accessing to the target levels of 100% and 61.8% and 50% is equal to 62.32%, and the failure rate is equal to 37.69%.

Based on the above discussion of the results, and after excluding the target levels of 23.6% and 38.2%, it is clear that the order of the most effective mathematical equations based on the overall rate of access to the target levels of 100% and 61.8 and 50% is as follows:

1. The target level of 100%: where the total ratio to access this target level was 34.05%, with an average profit of +11.83%.
2. The target level of 61.8%: where the total ratio to access this target level was 17.91%, with an average profit of +6.57%.
3. The target level of 50%: where the total ratio to access this target level was 10.36%, with an average profit of +5.15%.

Conclusion

This study aimed mainly to complete the missing part in the Japanese candlestick patterns, which is to calculate the target levels by developing effective mathematical equations to determine the expected target levels, depending on patterns confirmation filters, to identify the most effective cases when applying these equations, and to determine the most effective of these equations. The study concluded the following:

1. The most effective cases applicable to calculating the target levels depending on Patterns confirmation filters are the cases that contain between 4 and 7 candles inside filters respectively, where the percentage of success in accessing one of the target levels was 88.71%, with a profit rate ranging from +1.45% to +12.44%, and the rate of the time period to access the target levels ranged from 2 to 38 trading days. On the other hand, the failure rate to access one of the target levels was 11.29%, with loss rate ranging from -3.99% to -4.01%, and the rate of the time period to closing below or above the stop loss and failure to access the target levels was approximately equal to 7 trading days.
2. For the cases containing between 4 and 7 candles inside filters, in general, the most effective mathematical equations for determining the expected target levels depending on patterns confirmation filters are 100% and 61.8% and 50% respectively, where the rate of success in accessing one of these levels is equal to 62.32%, with the profit rate ranging from +5.10% to +12.44%. On the other hand, the failure rate to access one of these levels is equal to 37.69%, with the loss rate ranging from -3.99% to -4.01%.
3. The most ineffective cases applicable for calculating the target levels depending on patterns confirmation filters are the cases that contain 8 and 9 candles inside filters respectively, because the failure rate of these cases is larger than or equal to the success rate.
4. The lowest frequency cases applicable for calculating the target levels depending on patterns confirmation filters are the cases that contain 10 candles inside filters, where the rate of appearance of these cases was only 3.29% of the total cases of the study.
5. For the cases containing 4 candles inside filters, the most effective mathematical equations for determining the expected target levels depending on patterns confirmation filters are 100% and 61.8% respectively, where the rate of success in accessing one of these levels is equal to 62.13%, with the profit rate ranging from +4.54% to +9.46%. On the other hand, the failure rate to access one of these levels is equal to 37.87%, with loss rate ranging from -3.82% to -3.87%.
6. For the cases containing 5 candles inside filters, the most effective mathematical equations for determining the expected target levels depending on patterns confirmation filters are 100% and 61.8% and 50% respectively, where the rate of success in accessing one of these levels is equal to 60.26%, with the profit rate ranging from +5.03% to +12.66%. On the other hand, the failure rate to access one of these levels is equal to 39.74%, with loss rate ranging from -3.50% to -4.03%.
7. For the cases containing 6 candles inside filters, the most effective mathematical equations for determining the expected target levels depending on patterns confirmation filters are 100% and 61.8% and 38.2% and 50% respectively, where the rate of success in accessing one of these levels is equal to 61.38%, with the profit rate ranging from +4% to +17.22%. On the other hand, the failure rate to access one of these levels is equal to 38.62%, with loss rate ranging from -4.06% to -4.07%.
8. For the cases containing 7 candles inside filters, the most effective mathematical equations for determining the expected target levels depending on patterns confirmation filters are 100% and 61.8% and 38.2% and 50% respectively, where the rate of success in accessing one of these levels is equal to 58.91%, with the profit rate ranging from +6.40% to +20.55%. On the other hand, the failure rate to access one of these levels is equal to 41.09%, with loss rate ranging from -4.40% to -4.79%.
9. For the cases containing 8 candles inside filters, the most effective mathematical equations for determining the expected target levels depending on patterns confirmation filters are 100% and 61.8% and 38.2% and 50% respectively, where the rate of success in accessing one of these levels is equal to 45.66%, with the profit rate ranging from +7.70% to +26.85%. On the other hand, the failure rate to access one of these levels is equal to 54.34%, with loss rate ranging from -3.98% to -4.47%.
10. For the cases containing 9 candles inside filters, the most effective mathematical equations for determining the expected target levels depending on patterns confirmation filters are 100% and 61.8% and 38.2% and 50% respectively, where the rate of success in accessing one of these levels is equal to 47.73%, with the profit rate ranging from +7.81% to +29.92%. On the other hand, the failure rate to access one of these levels is equal to 52.28%, with loss rate ranging from -4.11% to -4.43%.
11. For the cases containing 10 candles inside filters, the most effective mathematical equations for determining the expected target levels depending on patterns confirmation filters are 23.6% and 100% and 38.2% and 61.8% and 50% respectively, where the rate of success in accessing one of these levels is equal to 61.38%, with the profit rate ranging from +5.43% to +32.07%. On the other hand, the failure rate to access one of these levels is equal to 38.62%, with loss rate ranging from -3.93% to -4.02%.

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Notes

[1] Where Nison (1994, 2001, 2003) and Logan (2008) stressed that Japanese candlestick patterns do not have target levels based on the same patterns.

[2] Within the limits of a researcher's knowledge, Bulkowski (2008) is the only reference who explained explicitly two methods for determining target levels for Japanese candlestick patterns. The first method calculates the height of a Japanese candlestick pattern, and then adds or subtracts this height from the level of confirmation filter. In the second method, Bulkowski conducted separate statistics for all Japanese candlestick patterns to determine the rate of the achieved target level based on the traditional method (the pattern's height). Based on that, Bulkowski multiplied the height of Japanese candlestick pattern in the pattern's rate to achieve the target level based on the traditional method, and then added or subtracted the result from the level of the confirmation filter. And the method used in this study is characterized by it taking into account the number of candles that closed between the upper filter level and the lower filter level, including candles of Japanese candlesticks patterns. Whenever the number of candles represents the time factor, the larger the number of candles; whenever the longer time period; and whenever the expected target level farther, and vice versa, the fewer the number of candles; whenever the shorter time period; and whenever the expected target level closer.

[3] Financial Times 500 Ranking Report: An annual snapshot of the world's largest companies to show how corporate fortunes have changed in the past year, highlighting relative performance of countries and sectors. The companies are ranked by market capitalization and classified in six sections: Global, United States, Europe, United Kingdom, Japan, Emerging Markets. When the market capitalization of the company is larger, the ranking will be higher. (Source: The Financial Times website: http://www.ft.com. Date of visit and data download: 19 July 2014.)

[4] As referred to this by Pring (2002), Fischer & Fischer (2003), Morris (2006), and Logan (2008).

[5] This condition is called rise or decline, rather than uptrend or downtrend, and is determined by the rise or decline by five successive rising or falling days at least before the appearance of the Japanese candlestick pattern, consistent with Pasternak (2006), who explained that the secondary trend lasts from 5 to 15 days, and consistent with Bulkowski (2008), who noted that the trend in the ideal situation would be from 3 to 7 days. Also, Nison (2001) explained in his comments on some of technical charts that the rise or decline could be determined by two or three rising or falling candles at least. In addition to that, the determination of the rise or decline by five rising or falling days is at least consistent with charts and examples described in specialized books in the field of Japanese candlesticks, such as Pring (2002), Morris (2006), Rhoads (2008), and Lambert (2009).

Constructing Optimal Momentum Systems — Optimize or Diversify?

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Abstract

This article aims to present empirical evidence on the application of a simple momentum strategy based on moving averages to major equity market indices. This is done through adjusting moving averages, and evidence is presented on whether the bulk of the return comes from the long or short trades and finally, whether it is better to optimize the parameters selected or to diversify over many different combinations of parameters. The research that has been found suggests that both long and short trades generate significant returns and also suggests some value in optimizing the parameters used in a momentum strategy based on the recent past.

Introduction

The Momentum Strategy

The core concept in technical analysis is moving averages, and it dates back to the 18th century, founded by a mathematics historian, Jeff Miller. During the mid/late 18th century, moving averages became popular in the finance sector for making the prices of markets comprehendible by creating a single flowing line to indicate the direction of a stock. This then was incorporated with momentum pioneered by Richard Driehaus (who is recognized as the father of momentum investing) and quotes that "far more money is made buying high and selling at even higher prices." This reinforces the idea momentum is based off, that is, once a trend is established, it is more likely that it will carry on in that direction than move against the trend.

Key Research Questions

Throughout the research, the study has revolved around three prime questions:

1. What timeframe when using moving averages works best to generate the most returns?

   As moving averages are a large facet of the momentum strategy, we should outline the most effective speed (timeframe) to use. This would be done through testing different moving averages on historical prices, varying the fast and slow speeds, and then picking the speeds that generate the most returns.

2. Is longing/shorting making the most returns/losses, and therefore is it better to enter trade to only long/short or in tandem?

   It may be that there is a pattern of long-term trading with the profits gained from shorting and longing and thus, it is questionable whether the combination or the separation of the two is better. For example, taking long signals may generate most of the profit, whereas taking short signals reduces the returns, and thus it is wise to only take the long signals.

3. Is it better to diversify the moving averages or to optimize the few moving averages?

   Upon filtering out the highest return generating moving averages, the final question is whether we should place it into different portfolios or concentrate it into a couple. By diversifying we are reducing the risk and reducing the reward, vice versa for when we optimize.

Application

A prominent use of momentum investing is in CTA funds/hedge funds. About two-thirds of CTAs use momentum to dictate whether they buy or sell. Namely, BarclayHedge said that systematic trading (also momentum investing) is the most commonly employed strategy, representing $269.33 billion in AUM. As a concept, it is deemed as a reliable method to signal and predict future trends; however, in practice, other indicators are used in tandem with momentum.

Literature Review

Momentum as a concept has been appreciated since the 1990s and has been utilized as a primary method for profits in many funds, as highlighted in the application section. Developing the strategy has occurred throughout the past decades, whereby researchers have employed momentum in different situations and in different manners to examine the best conditions to apply momen°tum. The majority of the results are reassuring to suggest that momentum is a method of return generation.

Jegadeesh and Titman (1993) were one of the first to explore the effectiveness of momentum and to document it in their *Returns to Buying Winners and Selling Losers—Implications for Stock Market Efficiency.* The study reinforces that buying recent winners and selling recent losers is rather an effective strategy. The results collated depict that abnormal returns are realized when a six-month timeframe is used to dictate whether to hold or to sell for the next six months. This represented an average of 12.01% of returns per annum. However, the following two years reveals that the returns dissipate and reminds us that momentum strategies that focus on recent winners and losers make money over short horizons of 3 to 12 months.

Leading on from Jegadeesh and Titman, several studies were conducted to explore momentum across foreign stocks (Rouwenhorst, 1998), across industries (Moskowitz and Grinblatt, 1999); across emerging markets (Rouwenhorst, 1999); across countries (Liu et al., 1999; Griffin et al., 2003); across asset classes (Okunev and White, 2003); and across equity styles (Chen and De Bondt, 2004). The studies conducted over the decade since Jegadeesh and Titman's study depicts and reinforces the profits of momentum over different facets in the markets.

Up to Antonacci (2012), momentum has been explored from using either cross-sectional momentum or timeframe momentum. In Antonacci's *Risk Premia Harvesting Through Dual Momentum,* he argues that using the two momentums in tandem with each other will enhance the returns. The results generated from the study portray exactly that, and further depict that using them in tandem makes diversification more efficient.

Following Li, Xiaofei; Brooks, Chris; Miffre, Joelle (2009), trading falling stocks is more "expensive" than trading booming stocks. Through this idea, the paper "Low-Cost Momentum Strategies" attempts to define a new momentum whereby there is a relationship between the transaction costs and the volume traded; this relationship only materializes when selling, not when buying. The results reinforce the idea that "the strategies that shortlist the 10%, 20% and 50% of winners and losers with the lowest total transaction costs generate average net returns of 18.24%, 15.84%, and 12.49%, respectively." (page 12).

The Fama–French three-factor model was a method of measuring market returns, and through research, it was uncovered that value stocks outperform growth stocks. Carhart (1997) provided an extension to the model and included another factor—momentum; more specifically, monthly momentum, and ultimately suggests that the four-factor model is predominantly a more effective method of predicting market returns.

Methodology

Signaling

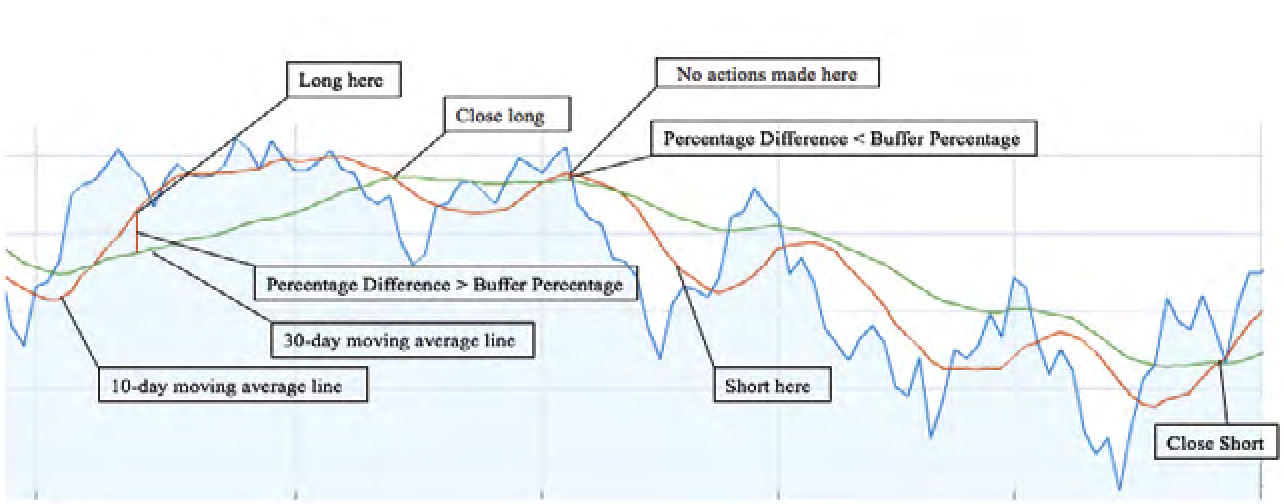
To put momentum into practice, we would need to know when to buy and sell through inference of the opening and closing prices. As exemplified by Figure 1, we first find the moving averages of the closing prices. The fast speed calculates a shorter timeframe of a moving average, and hence graphically, we would have a more volatile graph, whereas slow speed calculates a larger timeframed moving average and depicts, graphically, a smoother graph. When the fast speed exceeds the slow speed, this indicates that, perhaps due to the occurrence of an event, there is an unusually large price pulling the fast speed up, and this wherein we buy, as it can indicate a beginning of a new trend. Hence, when the difference between the fast and slow speed is negative, we sell. However, this is not reliable as if the difference is minuscule, then we should count it as negligible and not enter the trade; however, under this model we will still buy or sell. We must introduce some buffer, which was assigned to be 120%, whereby what differentiates the fast and slow speed must exceed 120% of the closing price.

Data

The information of popular indices was retrieved from Yahoo Finance, and the historical data of the market indices was used to test momentum. These market indices include FTSE 100, Nikkei 225, Shanghai Composite, S&P 500, DAX, NASDAQ-100, Hang Seng Index, and Russell 3000. To ensure that the gulf between the prices 50 years ago compared to today does not hinder the results, data from the indices were used in six-month timeframes rather than being inclusive of all the data. All the percentage profit and loss of each trade was utilized further to generate different statistics portrayed below for both slow speed and fast speed. The majority of the statistics, such as returns, number of trades, number of profitable trades, percentage of profitable trades and average return per trade, were used to indicate whether the momentum strategy (for different moving averages) was profitable or not. Others are explained below:

- Standard Deviation – This statistic measures dispersion and conveys whether the data points tend to be close to the mean percentage profit and loss. It is a useful indicator as to whether the return is generated due to smart investments or an increase in risk.
- Skew – The skewness is useful in suggesting whether there were occasional large gains and frequent small losses (positively skewed) or frequent small gains and occasional large losses (negatively skewed).
- Kurtosis – Similar to standard deviation, kurtosis also measures dispersion, but measures it away from the mean. The higher the kurtosis, the higher the probability for abnormal and lower returns to occur. Vice versa for a lower kurtosis.

Figure 1. Illustration of Momentum Investing



Results

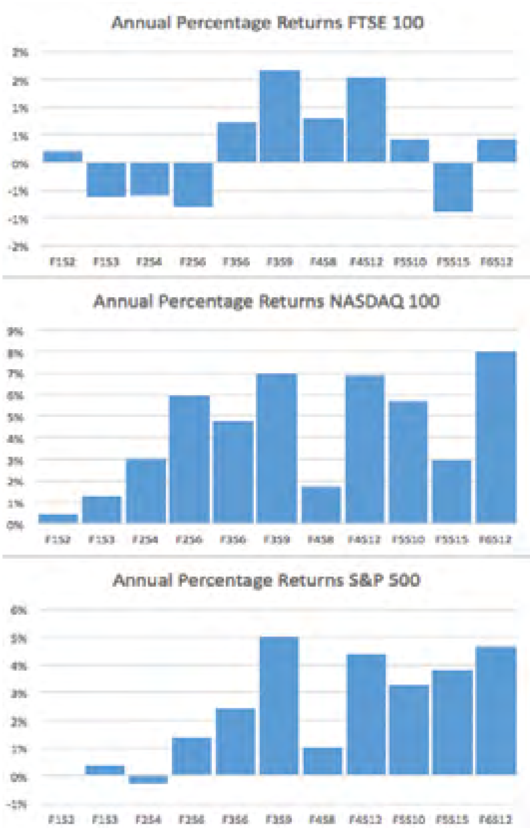
Analysis of Returns and Statistics

When trading back and forth, the largest indicator of whether the technique used is effective is through working out the average amount of returns received. In this paper, the returns are in percentages, allowing a way to predict future returns despite the amount invested.

In tandem with returns, the use of statistics is interlinked and is fundamentally the analysis of volatility and the assessment of whether returns are generated due to higher risk or from smart investments. Many graphical representations of both returns and statistics were used to illustrate the returns and the volatility of the returns.

By using the technique highlighted in the methodology, I created a stimulation tailored to use and to experiment on historical prices to see the returns generated from several moving averages.

Figure 2. Percentage Returns



*F1S2 = Fast Speed — 1 & Slow Speed — 2

As shown from Table 1 and the tables in Figure 2, the majority of the moving averages translate to a positive return. Table 1 then makes it simple to filter out the best performing moving averages across the three indices. However, this is not the only filter.

A limitation to using the mean of the returns is that it may not necessarily be representative of the returns the moving average can translate. This is because the markets are heavily affected by events that occur in our day-to-day lives. The negative percentage returns could be explained by the unexpected financial crisis in 2007, which subsequently lead to huge losses.

Table 1. Overview of Trading Strategy Results

Moving Average	Annual Percentage Returns from Index			Average
	FTSE 100	S&P 500	NASDAQ 100	
F1S2	0.19%	0.50%	0.03%	0.24%
F1S3	-0.60%	1.33%	0.34%	0.36%
F2S4	-0.59%	3.01%	-0.30%	0.71%
F2S6	-0.81%	5.93%	1.35%	2.16%
F3S6	0.73%	4.77%	2.37%	2.62%
F3S9	1.65%	6.99%	4.97%	4.54%
F4S8	0.80%	1.73%	0.99%	1.17%
F4S12	1.54%	6.90%	4.37%	4.27%
F5S10	0.43%	5.69%	3.29%	3.14%
F5S15	-0.88%	2.97%	3.83%	1.97%
F6S12	0.43%	7.99%	4.64%	4.35%

In this light, it is questionable whether we should commit to entering the trade to long or to short, as there is a possibility that, for example, longing creates most of the profits, and shorting, on average, makes negative profit. Then it would be wise to only enter the trade when momentum signals to long and not to enter when it signals to short.

Figure 3. Illustration of Returns From Short/Long in Six-Month Increments

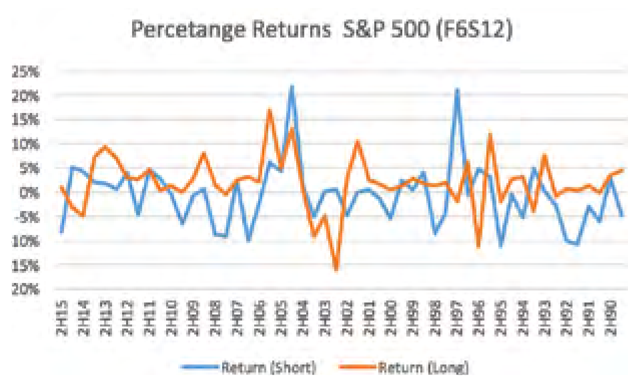
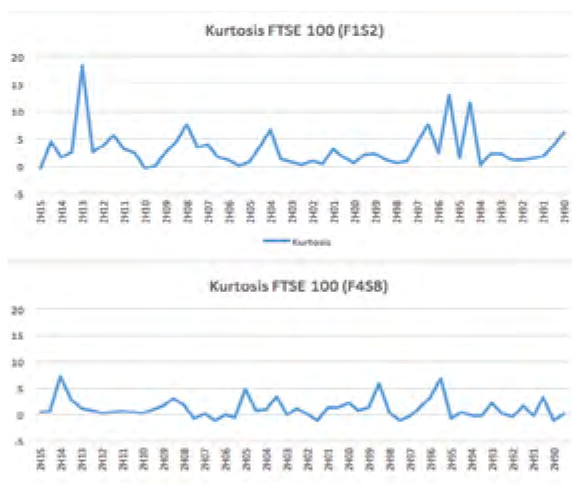


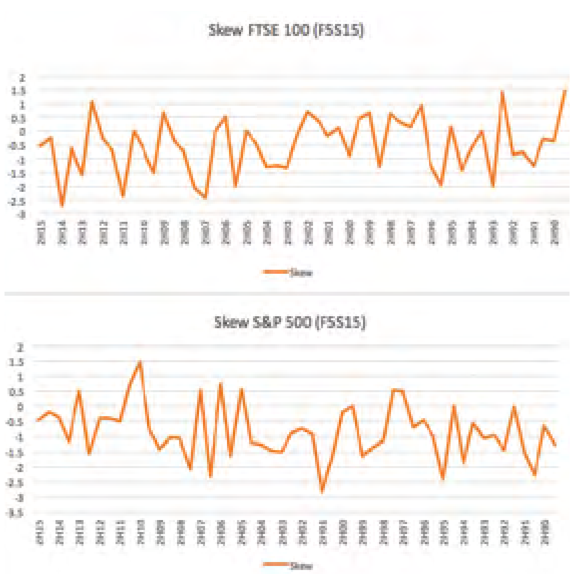
Figure 3 illustrates that the returns derived from entering the trade to short or to long are similar. From the average of percentage returns generated by short and by long, interestingly, they both derive a positive return. Thus, it would be better to use them in tandem than separate.

Figure 4. Illustration of Kurtosis in Six-Month Increments



Kurtosis as highlighted before indicates the level of tail risk, as a measure of the shape of the tail. In Figure 4, the average kurtosis for F1S2 is greater than in F4S8. As highlighted in the data part of this paper, the higher the kurtosis, the larger the tails in the distribution. In Figure 4, the lower kurtosis on average translates to a higher return than a higher kurtosis. This can be explained by the fact that higher volatility can lead to two consequences—greater abnormal returns or greater losses. It is clear that taking the risk of having greater losses outweighs the possible abnormal returns gained, and hence, a lower kurtosis is better. Interestingly, the pattern is true for the majority of the moving averages.

Figure 5. Illustration of Skew in Six-Month Increments



In Figure 5, there appears to be a clear relationship between negative skew and returns. As showcased from the line graphs, a majority of the returns are with negative skew, and this indicates that there were frequent small gains and large losses. Surprisingly, in the case of Figure 5, the only moving average associated with positive skew is the one generating the highest returns on average, which could indicate that a positive skew connotes to higher returns. And, it is true for many of the cases. However, keep in mind that skew is used in tandem with other performance statistics. This is because they formulate a way of indicating whether having higher volatility in your portfolio is necessarily a good thing, and that is similar for many of the statistics used.

Analysis of Application

Having used the information generated from the analysis of returns and statistics, five of the best moving averages were used on other indices to reaffirm the effectiveness of it. Table 2 showcases that most of the moving averages generated a positive return.

Table 2. Overview of Trading Results (Application)

	Annualised Percentage Returns				
	F3S6	F3S9	F4S12	F5S10	F6S12
NIKKEI 225	2.94%	5.37%	3.91%	1.94%	2.29%
HANG SENG	1.12%	4.02%	3.44%	1.44%	0.84%
DAX	2.66%	3.17%	2.58%	-1.13%	-1.98%
SSE COMPOSITE	-11.05%	-9.37%	-4.09%	-2.28%	-2.28%
RUSSELL 3000	2.02%	3.33%	5.44%	2.30%	3.93%

However, in practice, we must decide whether we would optimize or diversify across the moving averages. This has been depicted in Table 3, where the column is optimization, as we are only using one moving average, and the average of the row is diversification, as we are averaging the returns from the five moving averages. And, ultimately, optimization is a better method of using momentum. This could be due to the fact that trends tend to persist for longer than the period investigated, or it could be because the simple optimization approach captures the time-varying nature of trends in financial markets.

Table 3. Overview of Returns From Diversification and Optimization

Average (Col)		Average (Row)	
Mean	Median	Mean	Median
0.82%	2.22%	0.82%	1.24%

Conclusion

In this paper, I have provided empirical evidence that in most cases, momentum does generate positive returns, and I have answered all the prime questions in the paper on optimizing our use of momentum. This paper suggests that optimization is a better alternative to diversification; however, momentum is better used in tandem with other technical indicators, as momentum alone is not reliable due to its outlook based purely on quantitative factors, meaning that it oversees the qualitative factors like the Financial Crisis. To conclude, this study encourages optimizing momentum with the moving averages explored and considering the use of other indicators with momentum.

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Software and Data

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A Point-and-Figure Chart Study of the US Stock Market, 2015-16: The Wyckoff Method Applied

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Abstract

This article is the latest installment in the series of prediction studies using the point-and-figure data of the Down Jones Industrial Average (DJIA) to appraise primary bull and bear market accumulation and distribution. These studies apply the Law of Cause and Effect, which is a centerpiece of the Richard D. Wyckoff Method of Technical Market Analysis.

The current article reports the results achieved thus far in reaching the projections generated during the major accumulation base of 2009–2010. In addition an appraisal using the Wyckoff Method is made of a possible distribution top in the US Stock Market during 2016.

Introduction

This article shows that during the summer of 2015, the DJIA reached the 18,300 level, thereby entering into the upside price objective zone established during the 2008–2009 major accumulation base. Furthermore, at DJIA 18,300 during July 2015, a stepping-stone-confirming-count established during 2011 was fulfilled (See Figures 1 and 2). Figure 2 shows the price target zone where the distribution of long positions by the Composite Man could occur.

A test of Wyckoff point-and-figure projections first appeared in the *IFTA Journal* in 2004 with the article "Wyckoff Laws: A Market Test (Part A)." That first article in the series defined and illustrated the three basic laws of the Wyckoff Method and then applied them to the DJIA. The 2009 case study presented a

Figure 1. DJIA Minimum Upside Price Objective Zone Entered During 2015

continuation of the real-time tests of the Wyckoff Method.

In that first article, the spotlight zeroed in on the Law of Cause and Effect and the Wyckoff Method's application of the point-and-figure chart. It concluded with the expectation that the DJIA would rise from about 8,000 to around 14,400 during the 2003 primary-trend bull market.

The second article, appearing in the 2008 issue of the *IFTA Journal,* reported the successful achievement of the 2004 prediction. In 2007, the market reached within 5% of DJIA 14,400, and the article concluded that the empirical data generated by the DJIA, in that natural laboratory experiment of the market, supported the contentions of the Wyckoff Law of Cause and Effect.

Although no article was published to report on the top pattern that formed in the DJIA during 2007 and the subsequent decline into 2009, there nevertheless appeared a study after the fact. Mr. Brad Brenneise, a Wyckoff student at Golden Gate University, conducted a back-testing research project on the 2007 top and the subsequent drop to the low in 2009.

Using a point-and-figure chart of the S&P 500, Mr. Brenneise's study revealed that a point-and-figure count of the S&P 500 in 2007 gave an accurate forecast of the 2009 price low.

A companion article that fit into this Wyckoff series appeared in the *IFTA Journal* in 2010. The article, "Wyckoff Proofs," elaborated upon the concept of a "market test" that has occupied an important role in this series of studies of the Wyckoff Method. That 2010 article defined and illustrated three distinct types of Wyckoff Tests: (1) Tests as decision rules, such as the nine Buying Tests and the nine Selling Tests; (2) Testing as a phase in a trading range as seen in schematics of accumulation or distribution, and (3) Secondary tests as witnessed in the compound procedures of action and then test.

This, the fifth article in the series, harkens back to the article published in 2009 concerning the major cyclic top then underway. Like that article, which reported the results of the 2003–2004 prediction of an advance to 14,400, this article is another study of "what has actually happened." This article undertakes an examination of the interim results of the 2008–2009 accumulation base in the Dow Industrial Average, and emphasis is once again placed on the Wyckoff Law of Cause and Effect and the point-and-figure price projections for DJIA 17,600–19,200.

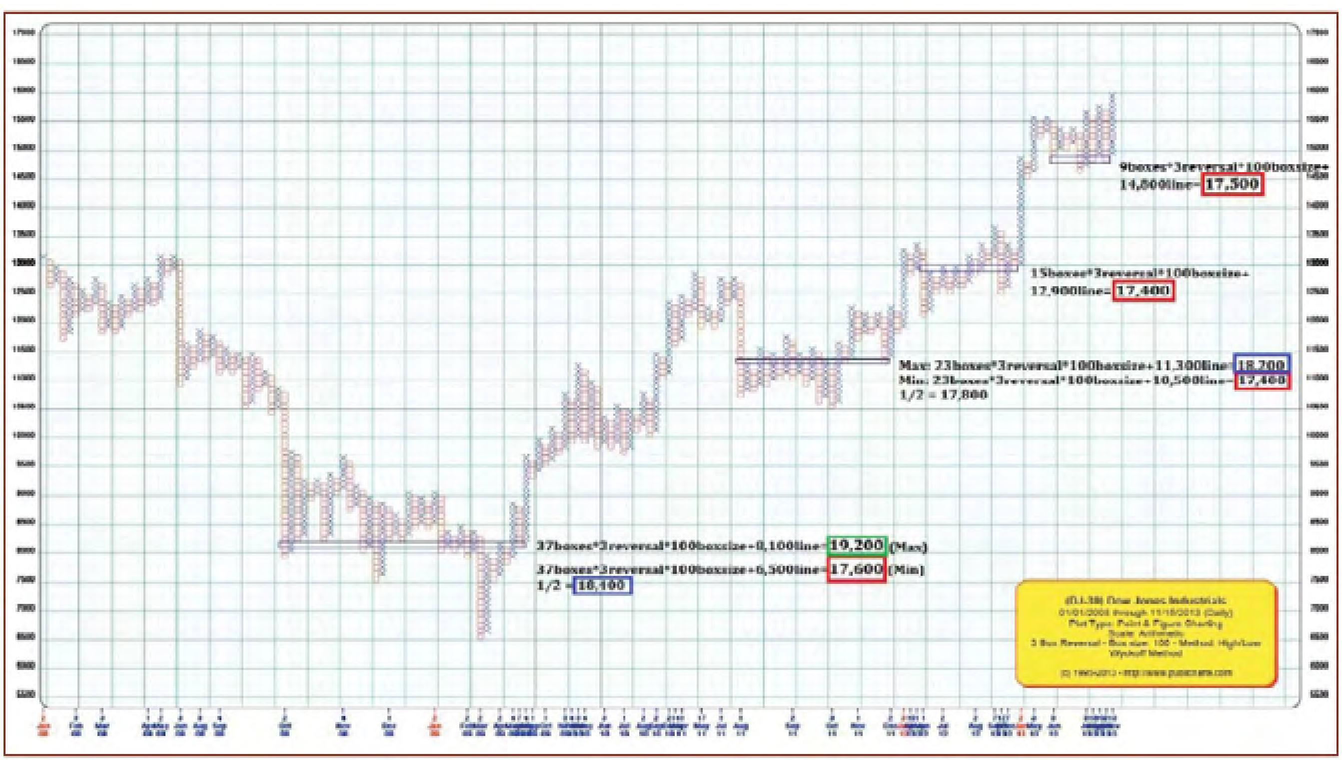
Richard D. Wyckoff and His Market Investment Theory

Richard D. Wyckoff was a titan of technical analysis. A pioneer in the technical approach to studying the stock market, Richard Wyckoff was a broker, a trader and a publisher during the classic era of technical analysis and trading in the early 20th century.

He codified the best practices of legendary traders, such as Jesse Livermore, into laws, principles, and techniques of trading methodology, money management, and mental discipline. Mr. Wyckoff was dedicated to instructing the public about "the real rules of the game," as played by the large interests behind the scenes. In 1930, he founded a school that later became the Stock Market Institute. Students of the Wyckoff Method have repeatedly time-tested his insights and found they are as valid today as when they were first promulgated.

Wyckoff believed that the action of the market itself was all that was needed for intelligent, scientific trading and investing.

Figure 2. Typical Market Campaign of Accumulation (2008–2009)



The ticker tape revealed price, volume, and time relationships that were advantageously captured by charts.

The Wyckoff Matrix: Coordinating Bar Charts With Figure Charts

Under the Wyckoff Method, it is significant for the technical analyst to appreciate that the Figure Chart (i.e., Point-and-Figure Chart) plays a supplementary and complementary role to the Vertical Line Chart (i.e., Bar Chart).

With its component of volume, the bar chart/vertical chart was looked upon by R.D. Wyckoff as a superior instrument for the diagnoses of trends and trading ranges. Therefore, the technician-trader should start with the bar chart, comparing successive waves of buying and selling, comprising price and volume, over time. That diagnostic process should reveal the relative power of demand vs. supply forces in the market. This diagnosis would uncover the bullish or bearish intentions of the powerful interests operating in the stock market. They were referred to as the "smart money" and conceptualized as "the composite man" or "the composite operator" by Wyckoff.

Wyckoff asserted that "three market laws" enabled the trader–analyst to discern the intentions of the dominant forces operating in a stock, commodity, or market as a whole. The first and by far the most prominent law was that of supply and demand. Simply stated, this law said that if demand was more powerful than supply, then price would rise. Likewise, if supply were dominant or in control, then prices would decline. Hence, the law of supply and demand was the proper concept to explain the present position and probable future trend of price in a market. Wyckoff counseled analysts and traders to rely on the Vertical Line or Bar Chart because it was the superior instrument for diagnosing small as well as large price swings in the market.

Closely allied to the law of supply and demand was the law of effort vs. result. When a divergence or disharmony between price and volume action occurred, the trader-analyst would become alert for a probable change in trend direction. Thus, the law of effort (volume) vs. result (price) was valuable for alerting the analyst–trader to an imminent change in trend direction.

The third law for ascertaining the intention of the Composite Man was the Law of Cause and Effect. Essentially, this third law said that a sideways trading range would create a cause, and the subsequent trend would be the result of that cause. Furthermore, the law stated that there existed a direct one-to-one proportion between cause and effect. Thus, for every effect, there would have been a preceding cause built up. In other words, the buildup of a cause in a trading range would measure the exact extent of accumulation or distribution. The resulting trend was then the realization of that buildup.

In sum, a significant quantifiable law linked the cause to the effect. The quantitative relationship between cause and effect was that of equal proportionality or a one-to-one relationship.

The instrument used by Wyckoff to measure the extent of a cause built up during trading range was the Figure Chart. A powerful and unique quantification was the special function of the figure chart, according to Wyckoff. During the early 1930s, Wyckoff and Associates promulgated guidelines for the proper construction of figure charts and the appropriate interpretation of figure charts. Those evolved into what ultimately became known as the Wyckoff Count Guide.

Both the figure chart and the bar chart grew out of the old-time trader's (19th and early 20th century) reading of the ticker tape of transactions. One of the initial appeals of the figure chart was its simplicity and ease for recording price changes. On the other hand, the bar chart was capable of displaying a rich array of price and volume activity. The bar chart was an excellent instrument for capturing the pulse of a market. The bar chart had the requisite sensitivity needed to discern the motives of the Composite Man on one side and the behavior of the crowd (i.e., the general public) on the other. The flow of information and logic placed the bar chart in a leading analytical position. The information furnished by the bar chart was ideal for the application of the law of supply and demand and for interpreting the law of effort vs. result.

In your own technical work leading to action, the bar chart should commence your analysis. This necessitates the proper interpretation of the phases within a sideways trading range. It is crucial to judge the culmination of the sideways trading range or the transition point separating markup from accumulation (LPS) or the last point of supply after distribution (LPSY). An excellent depiction of the Wyckoff Method of understanding the phases of a trading range was furnished in the widely read article that appeared in the 1994 issue of the *MTA Journal* (i.e., Jim Forte, CMT, "The Anatomy of a Trading Range").

Once the boundaries of a trading range have been established and the LPS or LPSY has been identified on the bar chart, the analyst–trader is then ready to consult the figure chart of the same trading range in order to conduct the quantification of the potential (i.e., "the count"). (See sidebar: The Wyckoff Count Guide.)

The Wyckoff Count Guide of Accumulation

Wyckoff Buying Tests: Nine Classic Tests for Accumulation*	
Indication	Determined From
1. Downside price objective accomplished	Figure chart
2. Preliminary support, selling climax, secondary test	Vertical and figure
3. Activity bullish (volume increases on rallies and diminishes during reactions)	Vertical
4. Downward stride broken (that is, supply line penetrated)	Vertical or figure
5. Higher supports	Vertical or figure
6. Higher tops	Vertical or figure
7. Stock stronger than the market (that is, stock more responsive on rallies and more resistant to reactions than the market index)	Vertical chart
8. Base forming (horizontal price line)	Figure chart
9. Estimated upside profit potential is at least three times the loss if protective stop is hit	Figure chart for profit objective

*Applied to an average or a stock after a decline. Adapted with modifications from Jack K. Huston, ed., Charting the Market: The Wyckoff Method (Seattle, WA: Technical Analysis, Inc., 1986), p. 87.

Simple count guide: Up count

After seeing a sign of strength (SOS), locate the LPS on a reaction, and count from right to left.

Detailed count guide: Up count

After having identified an SOS on the vertical line chart, locate the last point at which support was met on a reaction—the LPS. Locate this point on your figure chart as well and count from right to left, taking your most conservative count first and moving further to the left as the move progresses.

In moving to the left, turn to your vertical line chart and divide the area of accumulation into phases, adding one complete phase at a time. Never add only part of a phase to your count. Volume action will usually show where the phase began and ended.

As the move progresses, you will often see a lateral move forming at a higher level. Often, such a move will become a stepping stone confirming count of the original count. Thus, as such a level forms, you can often get a timing indication by watching the action of the stock as the potential count begins to confirm the original count. Resumption could begin at such a point.

For longer-term counts, you should add this count to the exact low or at a point about halfway between the low and the count line. You will thus be certain that the most conservative count is being used.

Counts are only points at which to "stop, look, and listen." They should never be looked upon as exact points of stopping or turning. Use them as projected points where a turn could occur, and use the vertical line chart to show the action as these points are approached.

In the case of a longer-term count, often the LPS comes at the original level of climax, and this level should be looked at first in studying the longer-term count. The climax itself indicated a reversal, with the subsequent action being the forming of the cause for the next effect. If the last point of support comes at such a level of climax, it usually makes it a more valid count. Often, the climax is preceded by preliminary support, and the LPS often occurs at the same level as the preliminary support.

The spring, which in this case is a number 3 spring or the secondary test of a number 2 spring, often constitutes the SOS and the LPS in the same action that is reached at the same point and at the same time. Usually, a spring will be followed by a more important SOS, and the reaction following that SOS is also a valid LPS.

Frequently, long-term counts on three- and five-point charts are confirmed by subsequent minor counts on the one point chart as the move progresses. Watch for this confirmation carefully, as it often indicates when a move will resume.

In the case of three-point or five-point charts, the same count line should be used as for the one-point chart.

A Case Study of the US Stock Market, 2009

An opportunity to apply the Wyckoff Laws and the Wyckoff Tests occurred in the US stock market during 2009. Figures 3 and 4 show the bar chart and the point-and-figure charts of the DJIA 2008-2009.

The reader is encouraged to use this application as a learning exercise. The laws of supply and demand can be seen operating on the weekly bar chart of the Dow Industrials (Figure 3). A definition of the uptrend, the line of least resistance, was revealed at around the 8,100 level for the Dow. Therefore, the expectation was for a bull market to unfold. At that same juncture of 8,100, a LPS was identified for which a count could be taken on the point-and-figure chart.

Once the LPS was identified, the Wyckoff analyst would turn to the point-and-figure chart of the Dow (Figure 4) to apply the Law of Cause and Effect and then make upside price projections. By counting from right to left along the 8,100 level, the analyst finds 37 columns. Since this is a three-box reversal chart, with each box worth 100 Dow points, the count becomes 37 × 300 = 11,100 points of cause built up in the 2008–2009 accumulation base. Added to the low of 6,500 the upside projection is to a price level of 17,600 on the Dow. Then, from the count 8,100 line itself, the accumulation base of 11,100 adds up to an upside maximum projection of 19,200.

The Wyckoff analyst should "flag" those upside counts on the point-and-figure chart of the Dow to provide a frame of reference that may help to keep the long-term trader/investor on the long side while the market undergoes inevitable corrections and reactions along its path toward 17,600–19,200. Of course, risk should be contained with trailing stop orders and the anticipation of further upside progress suspended or reversed with a change in the character of the market behavior that suggests the arrival of a bear market.

The Last Point of Support, the Count Line and Upside Price Projections to DJIA 17,600–19,200

The pullback or backup after the SOS on the bar chart of the Dow Jones Industrials defined the place on the point-and-figure chart to take the count. That count line turned out to be the 8,100 level on the 100-box-sized Dow Industrial point-and-figure chart. Along the 8,100 level, counting from right to left, there were 37 columns of three-point reversals, for a total point-and-figure count of 11,100 points accumulated during the 2008–2009 basing period. Using the Wyckoff Law of Cause and Effect and the Wyckoff Count guide (defined in the *IFTA Journal* 2008, page 14) one should add that 11,100 point count to the low of 6,500 to project a 17,600 minimum count. Adding that 11,100 point count to the count line 8,100 projects a maximum count of 19,200 (See Figure 4).

In conclusion, the expectation is for the Dow Industrials to rise into the price objective zone of 17,600–19,200 before the onset of the next primary trend bear market.

Conclusion

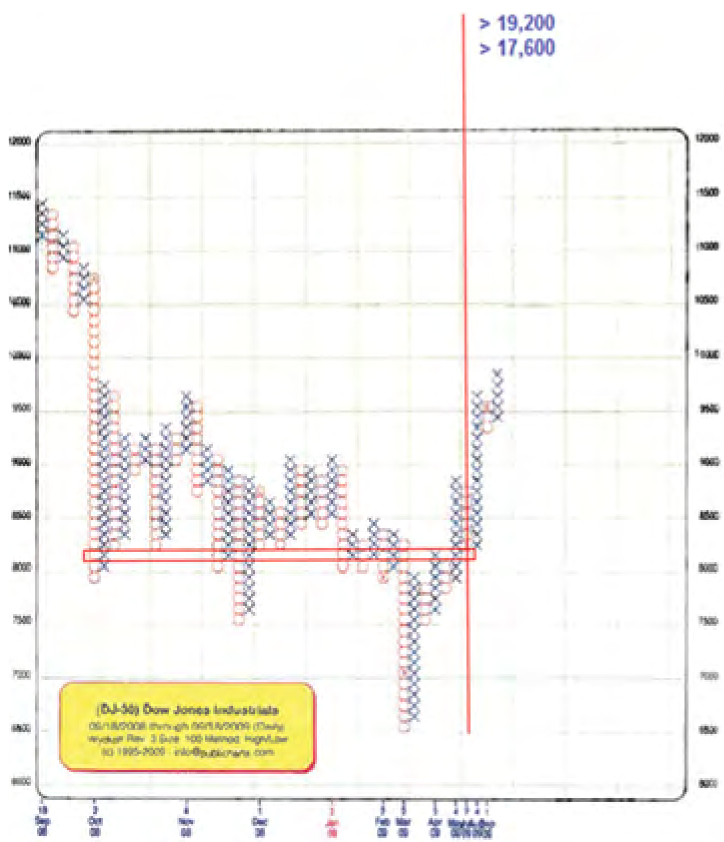
End Game: A Forked Road

During 2015–2016, the Composite Man might have induced a dramatic final rush upward to attract a broad public following. He could have "locked up the shorts" and seemingly "locked out" the late-arriving bulls by restricting corrections to around 6% DJIA or less. A virtual parabolic price rise into a "buying climax" within the price target zone seemingly occurred, and

Figure 3. Weekly Bar Chart of the Dow Industrials

By counting from right to left along the 8,100 level, the analyst finds 37 columns. Since this is a three-box reversal chart, with each box worth 100 Dow points, the count becomes 37 × 300 = 11,100 points of cause built up in the 2008—2009 accumulation base. Added to the low of 6,500, the upside projection is to a price level of 17,600 on the Dow. Then, from the 8,100 line itself, the accumulation base of 11,100 adds up to an upside maximum projection of 19,200.

Figure 4. Results of Applying Wyckoff Law of Cause and Effect and Wyckoff Count Guide



the distribution of long positions by the Composite Man to the public would have started somewhere within the price target zone of 17,600 to 19,200.

The *classic crowning formation* could frame this "end game" road pursued by the Composite Man (see the schematic in Figure 5). The Composite Man would keep a line of support—to help attract the laggards, for example the odd-lot public—until demand is exhausted. Heavy selling by the Composite Man and his emulators would occur after he had canceled his buying orders under the market. The Composite Man's *bear market campaign* could then commence at the Last Point Supply (LPSY).

During a classic crowning formation, like the one shown in Figure 5, volume expands and prices oscillate and a few stocks do record dramatic price gains. Smart, sophisticated traders should follow the path traveled by the Composite Man. Once long positions have been eliminated, they would wait for a *last point of supply* after a *sign of weakness* and then sell short.

But What If...

A second scenario could end up tricking a large number of investors and traders. That second scenario would envision a more pronounced correction of 10–20% within the current bull market (an equivalent to the 2011 shakeout). This could be followed by a final rise to the maximum DJIA figure chart price projection of 19,200. Perhaps ending with a final "Upthrust After Distribution" or UTAD (see Figure 5).

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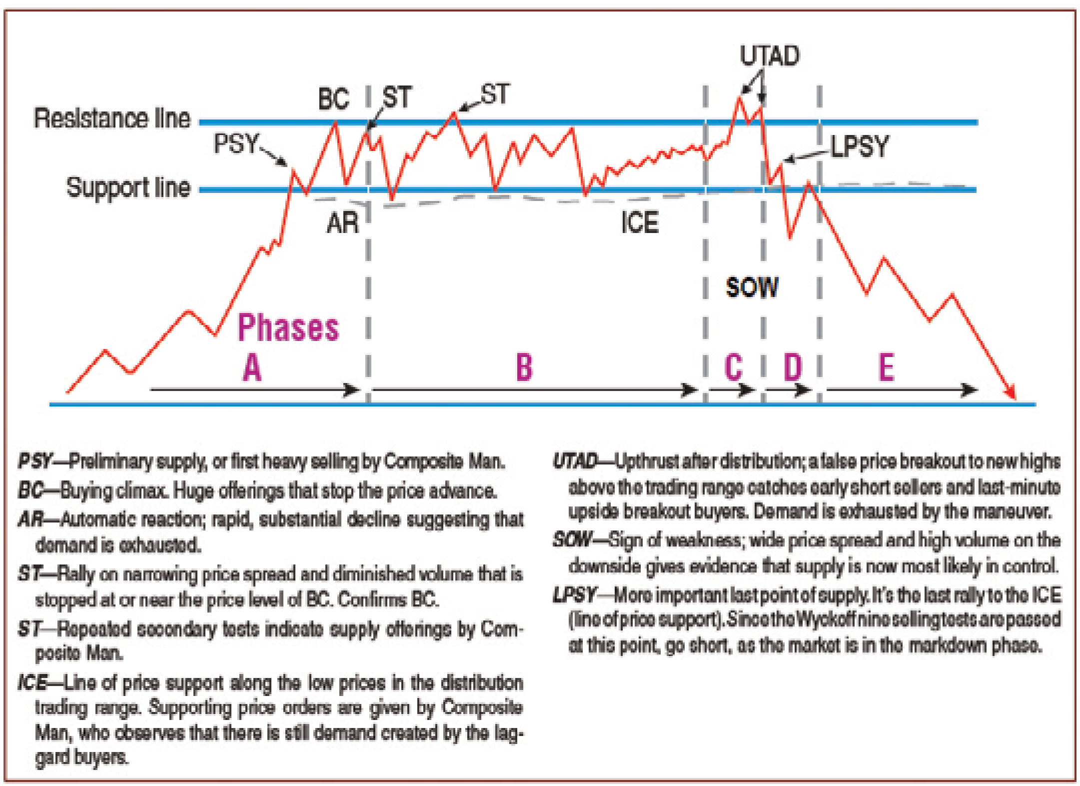
Author's note: The article gained its title, "The Wyckoff Method Applied in 2009: A Case Study of the US Stock Market," as it is based on a presentation by the same name that I gave at the 22nd Annual IFTA Conference in Chicago on October 8, 2009.

Figure 5. Crowning Formation

During a class crowning formation like this one, volume expands and prices oscillate between a support and resistance level. A few stocks record dramatic price gains.



An Empirical Comparison of Fast and Slow Stochastics

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Abstract

This paper compares the profitability of Stochastic Oscillators (STC) in 13 major stock market indices worldwide. We demonstrate, in contrast to common expectations, that the fast STC outperforms the slow STC in most markets, despite that fact that the latter can filter noisy trading signals while the former cannot.

Introduction

Technical analysis uses historical information to predict future price movement (Ellinger, 1971). Whether technical analysis can help investors beat the market and achieve abnormal returns has long been a controversial issue. The weak-form efficient market hypothesis (Fama, 1970) implies that technical trading rules should not be able to predict abnormal returns. However, there is also evidence supporting the predictive ability of technical trading rules. For example, Brock et al. (1992) showed that the moving average rule and trading-range breakout rule both work effectively on the Dow Jones Industrial Average. Chong and Ip (2009) showed that momentum strategies generate substantial profits for investors. Recently, there has been growing interest in nonlinear trading rules. Chong and Lam (2010) and Chong et al. (2012) showed that SETAR(200) and MA(50) rules perform well in the U.S. and China.

In this paper, the performance of Stochastic Oscillators (STC) is studied. The STC was developed by George Lane in the 1950s. It is a popular technical indicator, but there is a significant lack of studies conducted on it. A special feature of the STC is that it utilizes not only the information of closing price but also the highest and lowest prices in a given period (Murphy, 1999).[2] As the fast STC often generates noisy signals, a smoothed version of the fast STC, called the slow STC, is also commonly used by investors. In this paper, the profitability of the fast STC is compared with that of the slow STC. Surprisingly, the fast STC outperformed the slow STC in most markets, despite that fact that only the latter can filter noisy trading signals.

Stochastic Oscillator, %K and %D

The fast Stochastic Oscillator STC (*m,q*) consists of two parts, *m*-day %K and *q*-day %D. The *m*-day %K at time t is defined as follows:

$$\mathrm{FAST\%K}_m(t) = \frac{CP_t - MIN(LP_t,\dots,LP_{t-m+1})}{MAX(HP_t,\dots,HP_{t-m+1}) - MIN(LP_t,\dots,LP_{t-m+1})} \cdot 100 \quad (1)$$

whereCP_t CP_t, LP_t LP_t and HP_t HP_t are closing, lowest and highest price in day t respectively.

The *q*-day %D of *m*-day %K is defined as follows:

$$\mathrm{FAST\%D}_{m,n}(t) = \frac{\sum_{i=t-n+1}^{t}[CP_i - MIN(LP_i,\dots,LP_{i-m+1})]}{\sum_{i=t-n+1}^{t}[MAX(HP_i,\dots,HP_{i-m+1}) - MIN(LP_i,\dots,LP_{i-m+1})]} \cdot 100 \quad (2)$$

In this paper, the 3- and 5-day versions of %D are examined. The values of %K and %D are between 0 and 100. When %K is below 20 or above 80, the stock is considered oversold and overbought respectively (Lane, 1984). Note that %K is highly sensitive. It can easily achieve the boundary values of 0 and 100. For example, when the closing price reaches the highest position in time t, %K will be equal to 100. %D serves as a smoothed version of %K as well as a signal line. The crossing of %K and %D triggers a trading signal.

As the conventional fast version STC is sensitive to sudden price movements and often generates false trading signals, a slow version of STC(*m,p,q*) was proposed. In this paper, the slow %K at time t is defined as the *p*-day simple moving average of fast %K, i.e.,

$$\mathrm{SLOW\%K}_{m,p}(t) = \frac{\sum_{i=t-p+1}^{t}\mathrm{FAST\%K}_m(i)}{p} \quad (3)$$

The case where $p = 1$ corresponds to fast STC. In this paper, we let $p = 3$ for the calculation of the slow STC. The slow %D is defined as the *q*-day simple moving average of slow %K:

$$\mathrm{SLOW\%D}_{m,p,n}(t) = \frac{\sum_{i=t-n+1}^{t}\mathrm{SLOW\%K}_{m,p}(i)}{n} \quad (4)$$

The slow STC also ranges from 0 to 100.

Data and Methodology

The STC trading rules were applied to 13 major stock market indices. The data consists of daily high, low and closing prices. The details are listed in Table 1.

Table 1: The 13 Market Indices and Their Sample Periods

Index	Market	Sample Start	Sample End
Dow Jones Industrial Average	USA	16/11/1990	12/12/2008
S&P 500	USA	16/11/1990	12/12/2008
NASDAQ	USA	16/11/1990	12/12/2008
FTSE 100	United Kingdom	3/12/1990	12/12/2008
CAC 40	France	30/11/1990	12/12/2008
DAX	Germany	26/11/1990	12/12/2008
Nikkei 225	Japan	14/6/1990	12/12/2008
Hang Seng Index	Hong Kong	3/8/1990	12/12/2008
Straits Times Index	Singapore	8/9/1999	12/12/2008
KOSPI Composite Index	South Korea	7/7/1999	12/12/2008
TSEC weighted Index	Taiwan	6/7/1999	12/12/2008
SSE Composite Index	Shanghai	4/1/2000	12/12/2008
Hang Seng China Enterprises Index	Hong Kong	22/6/1999	12/12/2008

A trading signal is generated by the crossing of %K and %D in the overbought and oversold regions.[3] The oversold region is a region where both the %K and %D are below 20. A buy signal is triggered when %K rises above %D in the oversold region. Accordingly, a buy signal at time t can be written as follows:

$$\text{Buy: } \%K(t-1) < \%D(t-1) \;\; AND \;\; \%K(t) > \%D(t)$$

where both %K and %D are below 20.

The overbought region is defined as when both %K and %D are above 80. A sell signal is triggered at time t when %K crosses below %D in the overbought region, i.e.,

$$\text{Sell: } \%K(t-1) > \%D(t-1) \;\; AND \;\; \%K(t) < \%D(t)$$

where both %K and %D are larger than 80.

Short selling was accounted for and allowed during calculation of profit. A short position is taken when a sell signal is generated. If a trading signal arises, the next trading signal indicating the same action is ignored. Since there are around 250 trading days each year, the annual rate of return can be calculated as follows:

$$\text{Annual Rate of Return} = [(1+r_1)(1+r_2)\ldots(1+r_n)]^{250/T} - 1$$

where $(1+r_j)=S(j)/B(j)$. S(j) and B(j) are selling and buying price for the j-th transaction, n is the total number of transactions, and T is the number of trading days in the sample. For simplicity, transaction costs and cost of borrowing are not included in our calculations.

Results and Conclusion

Table 2 reports the annual rate of return generated by the STCs.

Table 2: Returns of the STC Trading Rules

	q	m=5	m=7	m=10	m=14	m=21	m=28	BH
Dow Jones								
Fast (*p*=1)	3	1.3 (102)	7.1 (126)	4.8 (119)	5.8 (116)	2.9 (103)	3.8 (81)	6.9
	5	**5.3** (47)	7.6 (72)	*10.9 (82)*	**7.6** (92)	**8.3** (81)	**7.3** (63)	
Slow (*p*=3)	3	**6.2** (62)	**10.2** (86)	**8.3** (101)	**7.2** (106)	**7.0** (91)	**7.5** (77)	
	5	3.2 (29)	**8.8** (43)	7.7 (65)	2.6 (64)	3.7 (61)	1.7 (55)	
S&P 500								
Fast (*p*=1)	3	5.4 (252)	**8.8** (216)	*9.3 (186)*	**8.9** (164)	2.4 (121)	2.6 (93)	5.8
	5	**7.2** (132)	**9.2** (141)	**7.3** (129)	4.7 (114)	**6.3** (99)	2.8 (73)	
Slow (*p*=3)	3	**7.8** (182)	6.1 (168)	6.3 (150)	5.8 (134)	**4.4** (103)	**2.6** (85)	
	5	3.0 (88)	4.1 (108)	2.0 (107)	**5.6** (102)	5.9 (93)	**3.6** (69)	
NASDAQ								
Fast (*p*=1)	3	**10.8**(278)	*12.4(242)*	**6.5** (188)	**2.5** (144)	**-3.6** (115)	**0.6** (93)	8.5
	5	**2.4** (144)	**9.3** (159)	**-3.1** (127)	**-1.7** (112)	**-1.6** (99)	**-0.6** (81)	
Slow (*p*=3)	3	2.8 (202)	3.3 (178)	3.2 (154)	-3.9 (128)	-5.4 (107)	-3.4 (89)	
	5	0.4 (105)	-4.3(115)	-6.1(115)	-3.9 (110)	-4.1 (99)	-3.2 (77)	
FTSE 100								
Fast (*p*=1)	3	**7.2** (268)	6.3 (239)	8.4 (209)	8.3 (157)	5.2 (123)	4.3 (98)	3.8
	5	**6.2** (145)	6.6 (147)	**9.3** (139)	**10.9** (123)	**7.5** (103)	**5.0** (80)	
Slow (*p*=3)	3	6.4 (191)	**8.3** (191)	**9.2** (165)	*11.4 (141)*	**6.4** (113)	**5.1** (94)	
	5	5.7 (99)	**8.3** (126)	6.7 (121)	7.1 (105)	7.4 (100)	3.3 (74)	
CAC 40								
Fast (*p*=1)	3	4.6 (245)	**6.6** (239)	*7.2 (201)*	**5.1** (157)	**-0.4** (119)	**1.6** (92)	3.9
	5	**2.0** (135)	**5.2** (135)	**2.7** (127)	**-0.8** (111)	**-0.7** (92)	**-0.8** (76)	
Slow (*p*=3)	3	**4.8** (185)	2.9 (179)	3.6 (161)	3.1 (135)	-0.1 (104)	0.4 (86)	
	5	-0.2(94)	0.9 (106)	-3.0 (98)	-2.6 (94)	-0.9 (90)	-1.3 (74)	
DAX								
Fast (*p*=1)	3	**4.5** (262)	*7.1 (238)*	**2.6** (198)	**1.9** (152)	**-1.1** (124)	-2.2 (99)	6.7
	5	-0.7 (144)	**2.0** (158)	**-3.5** (137)	**-0.2** (124)	-1.9 (99)	-0.4 (89)	
Slow (*p*=3)	3	-1.1 (182)	2.7 (186)	**2.2** (166)	-1.1 (138)	-4.9 (107)	**-1.8** (93)	
	5	**0.8** (107)	-4.2 (123)	-4.8 (119)	-4.0 (112)	**-1.4** (97)	**0.6** (89)	
Nikkei 225								
Fast (*p*=1)	3	**5.0** (263)	*9.4 (259)*	**8.4** (207)	6.5 (175)	4.5 (142)	**2.7** (114)	-7.3
	5	**1.4** (163)	**4.4** (169)	**6.1** (154)	**3.5** (143)	3.8 (118)	1.0 (96)	
Slow (*p*=3)	3	3.8 (199)	2.4 (203)	7.4 (183)	**7.0** (165)	**5.2** (132)	1.3 (106)	
	5	-0.2 (121)	1.6 (141)	0.7 (134)	1.8 (128)	**4.9** (110)	**1.1** (92)	

	q	m=5	m=7	m=10	m=14	m=21	m=28	BH
Hang Seng Index								
Fast (p=1)	3	**4.2** (293)	0.0 (247)	**3.5** (211)	**-1.1** (163)	**-2.3** (116)	-6.9 (88)	8.8
	5	**-3.8** (151)	**1.4** (159)	**-0.6** (152)	**0.6** (127)	**-2.0** (102)	**-1.5** (82)	
Slow (p=3)	3	2.1 (201)	**2.5** (195)	0.6 (175)	-1.2 (152)	-3.1 (114)	**-3.9** (84)	
	5	-6.2 (104)	-2.4 (124)	-5.2 (124)	-1.9 (125)	-3.3 (92)	-2.1 (80)	
Straits Times								
Fast (p=1)	3	***12.4*** (79)	**8.7** (117)	**5.9** (99)	3.7 (79)	**-1.5** (60)	**-4.3** (48)	-2.0
	5	**3.8** (76)	**5.1** (78)	**-0.7** (64)	**-1.3** (60)	**-3.4** (46)	-11.8 (32)	
Slow (p=3)	3	4.0 (82)	2.3 (80)	1.4 (70)	**5.2** (70)	-4.2 (46)	-9.8 (36)	
	5	-1.3 (43)	-4.3 (46)	-4.8 (48)	-3.7 (44)	-3.5 (40)	**-10.1** (32)	
KOSPI								
Fast (p=1)	3	**29.9**(141)	34.9(131)	**26.7**(111)	**24.4** (92)	-4.4 (55)	-7.3 (46)	1.5
	5	**16.3** (73)	**30.2** (81)	**20.4** (75)	**7.8** (61)	**-2.7** (45)	**-5.2** (36)	
Slow (p=3)	3	22.7 (97)	***36.0***(107)	17.2 (86)	14.5 (75)	**-1.7** (51)	**-2.9** (42)	
	5	6.4 (50)	9.3 (67)	11.8 (65)	-3.1 (49)	-7.7 (39)	-11.4 (34)	
TSEC								
Fast (p=1)	3	10.2(146)	12.5(136)	13.9(120)	**12.3** (94)	-5.9 (60)	-5.8 (51)	-6.6
	5	-3.1 (84)	**5.3** (90)	**4.9** (83)	-2.6 (64)	**-6.7** (49)	**-0.9** (45)	
Slow (p=3)	3	**12.9**(107)	*21.9*(113)	**17.2**(103)	8.8 (77)	**-1.9** (58)	**-3.0** (50)	
	5	**9.6** (67)	-0.8 (71)	0.0 (70)	**3.6** (62)	-9.3 (46)	-7.9 (42)	
SSE Composite								
Fast (p=1)	3	**-6.0** (111)	-11.8(93)	**-3.8** (86)	**2.2** (76)	**-10.1** (56)	-13.3 (42)	3.6
	5	**-9.1** (70)	**2.4** (74)	**-9.6** (60)	**-6.1** (56)	-18.0(42)	-13.1 (38)	
Slow (p=3)	3	-9.8 (85)	**-6.0** (81)	-14.3 (70)	-7.7 (66)	-15.4 (50)	**-11.5** (42)	
	5	-11.6 (46)	-8.7 (52)	-14.2 (48)	-12.6 (44)	**-16.5** (40)	**-13.1** (36)	
Hang Seng China Enterprises								
Fast (p=1)	3	***13.6***(124)	**-5.1**(108)	**9.4** (92)	**5.1** (78)	1.5 (62)	-13.7(46)	13.5
	5	-18.2 (52)	**-3.8** (66)	**-2.3** (66)	**8.8** (62)	**2.5** (52)	**-13.7**(36)	
Slow (p=3)	3	-0.6 (88)	-7.3 (86)	5.5 (78)	-4.2 (64)	**2.7** (62)	**-9.8** (46)	
	5	**-13.7**(40)	-13.6(44)	-6.3 (48)	3.8 (56)	-9.5 (46)	-18.3 (36)	

Notes for the interpretation of the data in Table 2 are as follows:

(i) The case where $p = 1$ corresponds to data derived from the fast STC.
(ii) Column 'q' denotes the parameter used to calculate fast and slow %D. Given the values of m, p and q, the annual rate of return was calculated.
(iii) The figures in parentheses are the numbers of transactions.
(iv) The column BH reports the buy-and-hold returns. Given the values of m and q, the bolded returns indicate the higher return value among returns generated by the fast STC and the slow STC.
(v) The highest return of the trading rule for each index is *italicized*. Note that the number of transactions generally falls when m, p or q increases. In particular, the STC with m = 7, 10 and 14 are more profitable. These trading rules generate considerable returns in most markets. Note that the rules do not perform well in the Hang Seng Index and SSE Composite Index.

A comparison of the performance of fast STC and slow STC is reported in Table 3. Except for the cases of the Dow Jones Industrial Average, FTSE and TSEC weighted index, the fast STC generally outperformed the slow STC. Therefore, although the slow Stochastic Oscillator can reduce the noisy signals as perceived by market participants, the performance of fast STC is better than that of slow STC in most markets.

Table 3: Comparison Between Returns Based on Fast STC and Slow STC

Index	Cases Where Fast STC Is Better	Cases Where Slow STC Is Better
Dow Jones Industrial Average	5	7
S&P 500	7	5
NASDAQ	12	0
FTSE 100	6	6
CAC 40	11	1
DAX	7	5
Nikkei 225	8	4
Hang Seng Index	10	2
Straits Times Index	10	2
KOSPI Composite Index	9	3
TSEC weighted Index	5	7
SSE Composite Index	8	4
Hang Seng China Enterprises	9	3

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Notes

[1] We would like to thank Jonathan Siu for able research assistance. All the remaining errors are ours. Corresponding author: Terence Chong, Department of Economics, The Chinese University of Hong Kong, Shatin, Hong Kong. Email: chong2064@cuhk.edu.hk. Webpage: http://www.cuhk.edu.hk/eco/staff/tlchong/tlchong3.htm.

[2] The inclusion of high, low and close prices provides a useful way for exploiting any latent Granger causality, which exists in high frequency data (Fiess and MacDonald, 2002).

[3] All the calculations are conducted in Excel.

Software and Data

Yahoo finance

Multivariate Regression Analysis: Considering the Relevance of Past Performance

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Abstract

Investors often use past performance as a major source of knowledge about an asset class or a particular investment manager. Past performance can tell us a lot about the tendencies of asset classes and managers, but its meaning should be evaluated with great care. Simply comparing performances over an arbitrary time period can give way to a pattern of return chasing that can severely detract from performance. In fact, the emotional behavior of changing investments based on past returns has been the topic of many publications and hours of research. This paper will provide a statistical perspective on the relevance of past performance. Specifically, I will show that multivariate regression analysis can successfully identify mathematical relationships between various past performance statistics and future returns.

Multivariate regression analysis is not a foreign concept to the financial industry. It has been utilized by technical and quantitative analysts for some time now. However, constructing and interpreting this type of statistical analysis can be obstacles to investors without technical backgrounds. With this in mind, I will give a description of each of the variables and results in the analysis, and inform the reader of what is necessary for a statistically significant prediction model. I believe that this insight will make the benefits of multivariate regression analysis accessible to a wider variety of investors.

I begin with a concise description of the assets used as representation for the sectors of the S&P 500. This description is followed by an explanation of the method used for calculating returns and the frequency with which they are calculated. These two variables—calculation and frequency—are often debated topics and can have material effects on the outcome of the analyses. In this paper, I will use a monthly return frequency to calculate a logarithmic return. These decisions are key to multivariate regression analysis and must be made before further analysis is completed, making comparison between the outcomes of using different frequencies and return calculations quite time-consuming. However, it does force this decision to be a forethought and lessens the bias that could be present if it were an afterthought.

Investors often select calculation time periods with hindsight bias by comparing different returns and selecting the one that looks the best at that point in time. To better answer the questions "What time period should be used for performance calculations?" and "How long is the prediction good for?" I will attach statistical significance to four different look-back time periods and four different future time periods and make an informed decision on which combination has the highest predictive capability. By modeling each of these combinations of time periods, we gain insight about the sensitivity of the analysis to the time period variable. I will show that varying levels of significance exist across the different time period combinations and select one pair to be the optimal time period combination. I will discuss results from each look-back analysis, but for brevity this will not be an exhaustive exposition.

Finally, I will display the predictive capability of employing a multivariate regression model from the optimal time period combination in an actively managed sector rotation trading system. The performance that results from this trading system outperforms the S&P 500 on a risk adjusted basis according to several well-accepted performance measures. This success is mainly due to the downside protection incurred by rotating through the US equity sectors via a rules-based decision-making process, while still participating on the upside. For further analytical rigor, I forward tested the trading strategy 36 months to verify the analysis with out-of-sample data. I will show that the trends discovered by multivariate regression analysis are also present in data excluded from the backtest. Ultimately, I will show that a rules-based trading system, supplemented with multivariate regression, is a viable alternative to investing in a passive index.

Introduction

Today, approximately $7.8 trillion in assets are benchmarked to the S&P 500, with $2.2 trillion invested in funds that seek to replicate the return of the Index. (SP Indices) I believe that too many investors have given up on an actively managed large cap allocation in their portfolios in favor of a market-cap weighted index fund. By electing to invest in the S&P 500 Index, whether through a mutual fund or ETF, investors have chosen to merely participate in the stock market while there is ample opportunity to outperform.

The allocation of the S&P 500 index is devised among 500 U.S. large cap companies, ranked by market cap. Approximately 80% of the entire U.S. market is contained within this index. (SP Indices) The S&P 500 is rebalanced occasionally and is monitored by a committee in accordance to the methodology laid out by S&P Dow Jones Indices. (SP Indices) As of December, 2015, the market-cap allocation (by GICS sector) is found in Table 1.

Table 1. Current S&P 500 GICS Sector Allocations

Information Technology	20.9%
Financials	16.6%
Healthcare	14.6%
Consumer Discretionary	13.1%
Industrials	10.1%
Consumer Staples	9.6%
Energy	7.1%
Utilities	2.9%
Telecommunications	2.3%

As you can see, over 50% of the S&P 500 is allocated to three sectors: Information Technology, Financials, and Healthcare. Due to their large weighting, the performance of these sectors has a greater impact on the return of the S&P 500 than those with smaller weighting. The Utilities sector, for example, had the highest monthly return 17 times in the last five years; Healthcare, Technology, and Financials had a *combined* total of 17 highest monthly returns over the same time period.[1] During the 17 months in which Utilities had the highest return, its excess return to the S&P 500 Index, on average, was over 4% per month! Since Utilities makes up less than 3% of the Index, its performance is hardly realized in an S&P 500 Index fund. This consequence is the basis for a sector rotation strategy and presents a question only an active manager can address: "How do I allocate to the right sector(s) at the right time?"

Underlying Data

Select Sector SPDR ETFs

I have chosen to use the total returns from the nine Select Sector SPDR ETFs as representation of the sectors that make up the S&P 500 Index. The returns were taken from Morningstar Direct.[2] To maintain a uniform ending point for each analysis, the calculations end on 11/30/2012 (three years prior to the end of our data set).

A list of the Select Sector SPDR ETFs is found in Table 2. Note that the Select Sector ETFs do not exactly replicate the GICS sectors found in Table 1, but for the purpose of this paper, the Select Sector SPDR ETFs achieve the same effect, which is to divide the S&P 500 holdings into non-overlapping subsets. As a matter of fact, the Select Sector SPDR ETFs were developed exactly for this purpose: to allow investors to construct their own allocation of the well-known large cap S&P 500 stocks based on their specific investment goals and strategies. (Sector SPDR)

Table 2. SPDR Select Sectors

XLV	Healthcare
XLI	Industrials
XLY	Consumer Discretionary
XLP	Consumer Staples
XLB	Materials
XLK	Technology
XLU	Utilities
XLE	Energy
XLF	Financials

Return Calculation

The two most common measures of return are the geometric average return and the arithmetic average return. However, most discussion between the two may not adequately advise practitioners about the proper use of these concepts when forecasting future returns. (Hughson et al., 2006)

The input data in this paper includes a future cumulative return variable and therefore requires sensitivity with regard to the calculation used. University of Colorado, Boulder professors Eric Hughson, Chris Yung, and Michael Stutzer made a statement on the topic of forecasting returns:

> *Those wanting to forecast a typical future cumulative return should be more interested in estimating the median future cumulative return than in estimating the mathematical expected cumulative return. For that purpose, continuous compounding of the mathematical expected logarithmic return is more relevant than ordinary compounding of the mathematical expected return.* (Hughson et al., 2006)

Therefore, I have chosen to use the logarithmic return calculation. The logarithmic return *R* is defined as

$$R = ln(\frac{V_f}{V_i}) \tag{1}$$

where Vi is the value of the asset at the beginning time period, V_f is the value of the asset at the ending time period, and *ln*() is the natural log function.

A discussion on the frequency used for measuring the return will not be presented in this paper. For practical purposes, I have chosen to use a monthly return interval as the foundation for the analyses.

Introducing Multivariate Regression

Here, I will describe some of the key terms involved in multivariate regression. Stata's[3] mvreg (multivariate regression) command takes the independent and dependent variables for each sector at every time period and finds a straight line that best fits the data. Then, as output, mvreg calculates a regression coefficient[4] for each independent variable and gives a summary of how well the overall model and each variable predicted the future returns.

Independent Variables

I chose these five independent variables for their logical application to how investors evaluate assets.

Return was selected as an independent variable because investors often make choices based on the historical returns of an asset. These multivariate regression analyses will help put some science behind the claim, "Past performance cannot guarantee future results." Each trailing return variable will be defined using the same calculation as Equation (1)

$$Return_{t-x}(Sector) = ln(\frac{V_t}{V_{t-x}}) \tag{2}$$

where x is the look-back period and t is the current month.

Volatility is often associated with risk, and investors often measure the performance of an asset based on how well they are compensated for that risk. I used sample standard deviation instead of the population standard deviation due to the small number of observations used in each calculation, this is defined as

$$s_{t-x}(Sector) = \sqrt{\frac{1}{N-1}\sum_{i=t-x}^{t}(x_i - \bar{x})^2} \tag{3}$$

where x is the look-back period, t is the current month, $x_i = x_{t-x}, \ldots, x_t$ are the observed monthly logarithmic returns, x is the mean of these values, and N is the size of the sample. In Microsoft Excel, this is simply computed by the function "STDEV.S()".

Drawdown, which is also used as a measure of risk, is defined as

$$Drawdown_{t-x}(Sector) = Min(0, Return_{t-x}(Sector))$$

where Min(y, z) is a function that chooses the smallest of the two variables, x is the look-back period, and t is the current month. Essentially, $Drawdown_{t-x}$ will be set equal to 0 if $Return_{t-x}$ is positive or it will be set equal to $Return_{t-x}$ if $Return_{t-x}$ is negative. This will give us an idea as to whether downturns in the market are likely to continue, or if there is some form of mean reversion[5] taking place.

The regression slope is a function defined as

$$LinRegSlope_{t-x}(Sector) = \text{LINEST}(V_{t-x}, \ldots, V_t)$$

where x is the look-back period and t is the current month. "LINEST()" is a function in Microsoft Excel that calculates the statistics for a line by using the "least squares" method to find the slope of a best fit straight line through the values. This measure was chosen as a way to quantify the rate of change over time in the price of an asset.

The fifth and final independent variable is the excess return between the respective sector and the S&P 500, which is simply

$$EXRET_{t-x}(Sector) = Return_{t-x}(Sector) - Return(S\&P500)_{t-x}$$

where x is the look-back period and t is the current month. If the past return of the asset is greater than the S&P 500, this will be a positive number, and if it is less than the S&P 500, it will be negative.

Dependent Variables

This analysis attempts to explain the variation in the dependent variable using the independent variables at each new time period. Specifically, the dependent variables are the future returns of each sector over four different time periods: 3 months, 6 months, 12 months, and 36 months. They are calculated using the equation

$$Return_{t+k}(Sector) = ln(\frac{V_{t+k}}{V_t})$$

where V_t and V_{t+k} are the asset values at the beginning and the end of the future return length, respectively.

Regression Coefficients and Formula

Now, I will define each of the regression coefficients as well as present the regression formula using an x-month look back and a k-month future return.

- Define β_0 as the intercept.[6]
- Define β_1 as the coefficient for $Return_{t-x}$,
- Define β_2 as the coefficient for S_{t-x},
- Define β_3 as the coefficient for $Drawdown_{t-x}$,
- Define β_4 as the coefficient for $LinRegSlope_{t-x}$,
- Define β_5 as the coefficient for $EXRET_{t-x}$, and
- Define $Return_{t+k}$ as the prediction of return over the next k months.

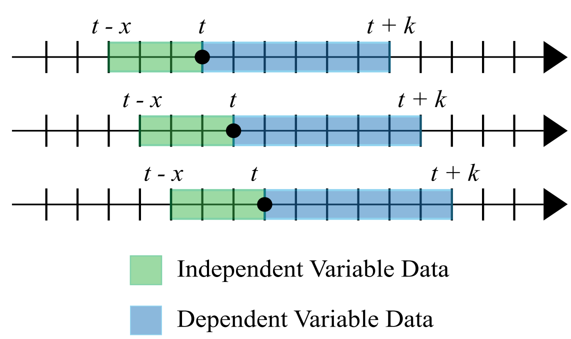
The regression coefficients and independent variables are plugged into the regression equation for $Return_{t+k}$:

$$Return_{t+k} = \beta_0 + \beta_1 Return_{t-x} + \beta_2 S_{t-x} + \beta_3 Drawdown_{t-x} + \beta_4 LinRegSlope_{t-x} + \beta_5 EXRET_{t-x}.$$

This is the standard multivariate regression model formula. The righthand side of this equation includes the regression coefficients suggested by mvreg and are each multiplied by their respective independent variable. The lefthand side of this equation (the result) is the predicted value for the specified future return.

Figure 1 gives a visualization of the calculation process. One month at a time, the multivariate regression analysis uses the independent variables to attempt to find a mathematical relationship to the dependent variables. Each of these statistical models are summarized by various measures of fit.

Figure 1. As the current time period changes, so do the time periods that are used to calculate the input variables.



Measuring Goodness of Fit

To answer the question, "Which predictions are valid and why?" I will explain several measures of "goodness of fit."

The root mean squared error (RMSE), the coefficient of determination (R^2), and the F-ratio are all calculated by mvreg to suggest which of the overall models have predictive capability.

The RMSE, also called forecasting error, is the spread between the actual future returns and the predicted future returns. In other words, it is the average distance between the best fit line and the predicted returns. RMSE is always between 0 and 1, and its significance increases as it gets closer to 0. RMSE is only used to compare the forecasting errors of different time periods for a particular Select Sector SPDR ETF and not between the Select Sector SPDR ETFs.

R^2 is a popular measure in portfolio management and a key output of regression analysis. This value explains the proportion of the variance in the future return that is predictable from the independent variables. The R^2 value presented in this paper is the Adjusted R^2 value.[7] This measure is always between 0 and 1 and its significance increases as the value gets closer to 1.

The F-ratio is used to decide whether the overall model has statistically significant predictive capability. To determine the significance of the F-ratio, we can look at its associated p-value.[8] In this paper, we will look for p-values smaller than 0.01. If the F-ratio calculated by mvreg is significant, we can infer that the overall model has predictive capability.

After deciding which overall models have attractive measures of goodness of fit, we "drill" down into the model to look at the regression coefficient and t-statistic of each independent variable to determine why.

The regression coefficient is a factor that determines how each independent variable affects the dependent variable. For example, if the past return has a negative regression coefficient, the past return is modeled to decrease the prediction of the future return (mean reversion). In the opposite case, if the past return has a positive regression coefficient, the past return is modeled to increase the prediction of the future return. The regression coefficients are estimated parameters; therefore, mvreg also calculates an associated error term. This error term is called the Standard Error and is used to construct a confidence interval for what the true regression coefficient actually is.

The t-statistic is a ratio of the regression coefficient divided by its Standard Error. Similar to the F-ratio, the t-statistic has an associated p-value to help determine if it is significant or not. Later, I will use these measures to examine two of the mvreg output tables and reason through why one is a good predictor model and why the other is a poor predictor model (Table 9 and Table 10 in the 12-Month Look-Back Analysis section).

Optimal Time Period Analyses

3-Month Look Back Analysis

For a visualization of how the data is calculated, please refer to Figure 1, substituting x = 3 for the independent variable calculations and *k = 3, 6, 12, 36* for the dependent variable calculations.

Table 3 shows the p-values of F-ratios for each sector and their prediction of each future return variable. As you will recall, smaller p-values indicate greater significance. This table shows that there are a handful of p-values less than 0.01 scattered across different sectors and time periods.

The highest overall model significance is found in the 6-month future return for the Technology sector, $Return_{t+6}(XLK)$.

Table 4 shows XLK's regression coefficients and t-statistics for each independent variable, with the significant t-statistics in bold. From this table, we see that the intercept and the standard deviation contribute to this model's predictability. A significant intercept means that the average of the future returns is significantly different from zero. So, here the intercept indicates that $Return_{t+6}(XLK)$ tends to have positive returns on average for the time period given. The negative coefficient of $s_{t-3}(XLK)$ indicates that on average, high standard deviation has a significant negative impact on return over the next 6 months. Since the rest of the independent variables do not have significant t-statistics, we can conclude that their regression coefficients are not significantly different from 0.

The 3-month look-back period did result in some predictive capability, but there is no single time period combination that stands out as a clear winner. Three months is a short time period when it comes to past performance and is most likely the reason that the 3-month look-back provides the smallest number of significant results compared to the longer time periods.

6-Month Look-Back Analysis

The 6-month look-back produced a higher number of significant models than the 3-month look-back. Again, review Figure 1 for a visualization of the time periods used for data calculation, this time with x = 6.

From Table 5, we can quantify the overall model performance when compared to the other look-back periods by comparing their respective p-values of the F-ratios. When comparing p-values by column we see sectors such as XLK and XLF, where the p-values are significantly small across all future time

Table 3. 3-Month Look-Back Overall Model P-Values of F-Ratios for Each Regression Model

Equation	XLV	XLI	XLY	XLP	XLB	XLK	XLU	XLE	XLF
$Return_{t+3}$	0.0233	0.1254	0.6354	0.0249	0.4942	0.0053	0.0034	0.4138	0.1679
$Return_{t+6}$	0.0303	0.4758	0.776	0.2424	0.9627	0.0000	0.042	0.6683	0.3185
$Return_{t+12}$	0.0191	0.3134	0.0027	0.0056	0.2342	0.0001	0.1194	0.0315	0.0449
$Return_{t+36}$	0.0197	0.1301	0.0024	0.1149	0.0203	0.0015	0.7081	0.5803	0.0063

Table 4. Regression Results for $Return_{t+6}$(XLK) from 1/1/1999–11/30/2012

Sector	*Intercept*	$Return_{t-3}$	s_{t-3}	$Drawdown_{t-3}$	$LinRegSlope_{t-3}$	$EXRET_{t-3}$
XLK	0.09	-0.14	-1.71	-0.45	0.00	0.51
t-stat	3.53	-0.62	-5.07	-1.39	-0.09	2.17

Table 5. 6-Month Look-Back Overall Model P-Values for F-Ratios of Each Regression Model

Equation	XLV	XLI	XLY	XLP	XLB	XLK	XLU	XLE	XLF
$Return_{t+3}$	0.001	0.125	0.6069	0.2779	0.2055	0.0000	0.1104	0.2607	0.0002
$Return_{t+6}$	0.0977	0.0208	0.1064	0.1542	0.0129	0.0000	0.0059	0.0051	0.0000
$Return_{t+12}$	0.0858	0.0009	0.0002	0.0032	0.0004	0.0000	0.0009	0.0000	0.0000
$Return_{t+36}$	0.0012	0.0000	0.0000	0.0326	0.0001	0.0000	0.0007	0.0099	0.0008

periods. This means XLK and XLF are good candidates for using this look-back period. However, we are looking for a time period that gives small p-values across all of the sectors. Comparing the p-values across the rows, Table 5 shows that the 6-month look back is a much better predictor of $Return_{t+12}$ and $Return_{t+36}$ than it is a predictor of $Return_{t+3}$ and $Return_{t+6}$. The 12- and 36-month future returns are nearly all significant.

Table 6 shows each of the nine sectors' regression coefficients and t-statistics from the $Return_{t+12}$ model. If we count the number of significant t-statistics by column, we see that $Drawdown_{t-6}$ is a significant independent variable across five of the nine sectors; each has a negative regression coefficient. In the Independent Variables section, I defined that drawdown is either negative or 0, so these models are indicating that, on average, drawdowns over the past 6 months have a significant positive impact on the 12-month future return.

$EXRET_{t-6}$ is also a significant independent variable across five of the nine sectors. However, depending on the sector, the regression coefficient is positive or negative. A positive regression coefficient implies that an asset that has outperformed the S&P 500 for the last 6 months is likely to continue to do so over the next 12 months. A negative regression coefficient implies that an asset that has outperformed the S&P 500 for the last 6 months will tend to underperform in the next 12 months. This outcome gives an excellent reason why each sector has its own regression model; the independent variables do not affect each sector in the same manner.

When comparing the rows in Table 6, note that XLE and XLK have the highest number of significant regression coefficients. This doesn't come as too much of a surprise since these two sectors also had significant p-values in Table 5.

12-Month Look-Back Analysis

So far, increasing the length of the look-back period has increased the number of significant models. This will continue to be the case with the 12-month look-back period.

The overall model p-values of the F-ratios for each of the dependent variables are displayed in Table 7.

By comparing the p-values across the columns, we see a high number of sectors that have significant p-values, regardless of the future time period. If we compare the p-values by row, we see that the two longer return predictions have the smallest p-values overall.

Table 8 gives an in-depth look at the independent variables used in the 12-month future return model. $Drawdown_{t-12}$ and $EXRET_{t-12}$ appear most frequently. These are the same two variables that had statistical significance in the 6-month look back period. $Drawdown_{t-12}$ is significant in seven of the nine sectors, and $EXRET_{t-12}$ is significant in six. Similar to what we found in the 6-month look-back analysis, the regression coefficients of $Drawdown_{t-12}$ are all negative, and the regression coefficients for $EXRET_{t-12}$ are positive and negative.

Next, I will show the output computed by mvreg for XLE.

The top section of Table 9 shows the overall model goodness of fit statistics (RMSE, R^2, F-ratio, and p-value) when using the past 12 months to predict the next 6 months. The p-value of the F-ratio is highly significant, which suggests that this

Table 6. 6-Month Look-Back and $Return_{t+12}$—Regression Coefficients and T-Statistics

Sector	Intercept	$Return_{t-6}$	s_{t-6}	$Drawdown_{t-6}$	$LinRegSlope_{t-6}$	$EXRET_{t-6}$
XLV	0.04	0.11	-0.64	-0.91	0.00	0.13
t-stat	1.28	0.41	-0.82	**-2.55**	1.00	1.04
XLI	-0.08	0.62	1.18	-1.14	0.00	-0.55
t-stat	-1.77	1.99	1.59	**-3.54**	1.03	**-2.32**
XLY	-0.07	0.03	1.77	-0.67	0.00	0.22
t-stat	-1.66	0.09	**2.51**	-2.10	1.49	1.19
XLP	0.01	0.40	0.30	-1.01	0.00	-0.28
t-stat	0.54	1.30	0.41	**-2.94**	0.41	**-2.71**
XLB	-0.01	0.20	0.45	-0.85	0.00	-0.24
t-stat	-0.22	0.77	0.67	**-2.99**	0.68	-1.42
XLK	0.25	-0.86	-3.83	0.21	0.00	0.76
t-stat	**4.79**	**-2.65**	**-5.75**	0.58	0.00	**3.26**
XLU	-0.01	1.03	0.08	-1.25	0.00	-0.59
t-stat	-0.23	**3.17**	0.09	**-3.22**	0.02	**-3.92**
XLE	0.27	0.71	-3.09	-0.35	0.00	-0.58
t-stat	**4.52**	**2.71**	**-3.69**	-1.09	**-2.52**	**-2.92**
XLF	-0.09	-1.02	1.51	-0.21	0.00	0.44
t-stat	-1.97	**-3.21**	2.17	-0.65	**5.35**	1.77

Table 7. 12-Month Look-Back Overall Model P-Values for F-Ratios of Each Regression Model

Equation	XLV	XLI	XLY	XLP	XLB	XLK	XLU	XLE	XLF
$Return_{t+3}$	0.1128	0.0355	0.0923	0.0031	0.06	0.0063	0.0245	0.0000	0.0124
$Return_{t+6}$	0.4154	0.0014	0.0018	0.0001	0.0004	0.0001	0.0000	0.0000	0.0000
$Return_{t+12}$	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$Return_{t+36}$	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000

model has predictive capability. The bottom section of Table 9 shows the independent variables and their goodness of fit statistics (Regression Coefficient, Standard Error, t-statistic and p-value, and a 95% confidence interval for the true regression coefficient). All of the p-values of these independent variables are significantly contributing to the model.

In contrast, I present the mvreg output for XLV in Table 10.

Again, the top section shows the overall model goodness of fit statistics, and the bottom section shows the statistics of the independent variables. The p-value of the F-ratio of this model is not significant. This is enough to warrant exclusion from any predictive modeling, but if we look at the independent variables anyway, we see from the column labeled "P>|*t*|" that each of the p-values are too large to be considered significant, as expected.

36-Month Look-Back Analysis

The 36-month look-back gives results consistent with the 12-month look-back, but it doesn't have as many significant models.

Table 11 presents the R_2 values that are achieved using the 36-month look-back to predict $Return_{t+12}$ and $Return_{t+36}$. The

Table 8. 12-Month Look-Back and $Return_{t+12}$—Regression Coefficients and T-Statistics

Sector	Intercept	$Return_{t-12}$	s_{t-12}	$Drawdown_{t-12}$	$LinRegSlope_{t-12}$	$EXRET_{t-12}$
XLV	0.10	-0.14	-1.94	-0.67	0.00	0.29
t-stat	2.17	-0.64	-1.96	**-2.50**	**2.68**	**2.63**
XLI	-0.17	0.91	2.23	-1.17	0.00	-0.93
t-stat	**-3.36**	**4.05**	**2.61**	**-4.62**	-0.48	**-4.26**
XLY	-0.17	0.00	3.14	-0.82	0.00	0.14
t-stat	**-3.47**	0.00	**3.56**	**-3.55**	**2.59**	1.02
XLP	-0.01	0.50	-0.26	-1.52	0.00	-0.27
t-stat	-0.38	2.24	-0.34	**-6.17**	0.95	**-3.78**
XLB	-0.05	0.38	1.48	-0.50	0.00	-0.34
t-stat	-0.81	1.90	1.74	-2.09	-1.42	**-2.80**
XLK	0.35	-0.78	-4.96	0.25	0.00	0.56
t-stat	**5.48**	**-3.34**	**-5.00**	0.85	-0.62	**2.96**
XLU	-0.07	1.26	0.65	-1.35	0.00	-0.89
t-stat	-1.37	**5.26**	0.64	**-4.82**	-1.51	**-7.60**
XLE	0.29	1.17	-3.74	-0.76	0.00	-1.04
t-stat	**3.52**	**6.38**	**-3.05**	**-2.90**	**-5.65**	**-7.04**
XLF	-0.12	-0.54	1.59	-0.41	0.00	0.37
t-stat	**-2.43**	-2.09	2.04	-1.49	**3.89**	2.05

Table 9. mvreg — 12-Month Look-Back and $Return_{t+6}$(XLE)

XLE	**12-Month look-back**					
Overall Model	Obs. Parms	RMSE	R-sq	F	P	
$Return_{t+6}$(XLE)	156 6	0.18947	0.3851	18.78779	0.0000	
$Return_{t+6}$(XLE)	**Reg. Coef.**	**Std. Err.**	**t**	**P> |t|**	**95% Conf.**	**Interval]**
$Return_{t-12}$	1.17	0.184	6.38	0.0000	0.81	1.54
s_{t-12}	-3.74	1.228	-3.05	0.0030	-6.17	-1.32
$Drawdown_{t-12}$	-0.76	0.261	-2.90	0.0040	-1.27	-0.24
$LinRegSlope_{t-12}$	-0.0002774	0.00	-5.65	0.0000	-0.0003744	-0.0001805
$EXRET_{t-12}$	-1.04	0.147	-7.04	0.0000	-1.33	-0.75
Intercept	0.29	0.083	3.52	0.0010	0.13	0.46

Table 10. mvreg — 12-Month Look-Back and Returnt + 6(XLV)

XLV	**12-Month look-back**					
Overall Model	Obs. Parms	RMSE	R-sq	F	P	
$Return_{t+6}$(XLV)	156 6	0.09703	0.0325	1.00747	0.4154	
$Return_{t+6}$(XLV)	**Reg. Coef.**	**Std. Err.**	*t*	**P> |*t*|**	**95% Conf.**	**Interval]**
$Return_{t-12}$	-0.14	0.169	-0.82	0.4130	-0.47	0.19
s_{t-12}	-0.33	0.762	-0.43	0.6690	-1.83	1.18
$Drawdown_{t-12}$	-0.15	0.207	-0.72	0.4750	-0.56	0.26
$LinRegSlope_{t-12}$	0.0001237	0.00	1.15	0.2540	-0.0000896	0.0003371
$EXRET_{t-12}$	0.09	0.084	1.05	0.2940	-0.08	0.26
Intercept	0.03	0.034	0.88	0.3830	-0.04	0.10

R_2 values were not presented in the previous analyses, but XLP, XLY, and XLI achieve the three highest R_2 values in this paper, so we will take a look at them here. Using the past 36 months to calculate the independent variables resulted in models that were able to explain around 50% of the variance found in the 36-month future return of XLP, XLY, and XLI.

The p-values found in Table 12 explain the overall model significance. We see that the two longer future return models have more significance than the shorter two, purely by counting the number of significant p-values.

Table 13 shows the regression coefficients and t-statistics from the 36-month look-back period prediction for $Return_{t+12}$. As we saw in earlier analyses, $Drawdown_{t-x}$ and $EXRET_{t-x}$ play an important roll in the forward returns of most of the sectors. They are significant in five of the nine sectors in the same manner that they were in both the 6-month and 12-month look back periods.

Conclusion

These analyses attached statistical significance to five independent variables, over varying lengths of time, to determine how history can be used to predict future performance. In total, there were 16 unique combinations of time periods analyzed for their predictive capabilities. I evaluated the significance of the F-ratio for each to determine overall model predictability. Then, I further evaluated the independent variables of models where the F-ratio was significant.

The count of overall model significance can be summarized as follows: The 3-month look-back analysis produced a total of 9 significant F-ratios; the 6-month look-back analysis produced 23 significant F-ratios; the 12-month look-back analysis produced 29 significant F-ratios; and the 36-month look back analysis produced 25 significant F-ratios.

Since the 12-month look-back generated the highest number of significant models, I will choose this time period as the optimal look-back period. Within this look-back period, there is high significance in both the 12-month future return and the 36-month future return. However, I have chosen the 12-month future return as the optimal future return period.

Trading Strategy

Select Sector SPDR ETF Sector Rotation—Outline

Here, I give an outline of the rules for selecting the sectors, discuss the allocations and how they can change from month to month, and highlight the performance of the strategy compared to the S&P 500. This strategy will use an equal-weighted

Table 11. 36-Month Look-Back R^2 Values for $Return_{t+12}$ and $Return_{t+36}$

Equation	XLV	XLI	XLY	XLP	XLB	XLK	XLU	XLE	XLF
$Return_{t+12}$	0.1284	0.2520	0.2987	0.2164	0.1892	0.1000	0.2039	0.3733	0.2786
$Return_{t+36}$	0.1605	0.4505	0.5402	0.5503	0.2118	0.1645	0.2711	0.2896	0.2337

Table 12. 36-Month Look-Back Overall Model P-Values for F-Ratios of Each Regression Model

Equation	XLV	XLI	XLY	XLP	XLB	XLK	XLU	XLE	XLF
$Return_{t+3}$	0.0792	0.0645	0.0764	0.0524	0.0068	0.0135	0.2011	0.0002	0.0063
$Return_{t+6}$	0.7404	0.0155	0.0048	0.0096	0.0000	0.0818	0.0005	0.0000	0.0000
$Return_{t+12}$	0.0423	0.0000	0.0000	0.0000	0.0000	0.0196	0.0000	0.0000	0.0000
$Return_{t+36}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000

Table 13. 36-Month Look-Back and $Return_{t+12}$—Regression Coefficients and T-Statistics

Sector	*Intercept*	$Return_{t-36}$	s_{t-36}	$Drawdown_{t-36}$	$LinRegSlope_{t-36}$	$EXRET_{t-36}$
XLV	0.07	-0.07	-0.89	-0.60	0.00	0.22
t-stat	1.38	-0.3	-0.76	-2	1.96	1.7
XLI	-0.17	0.88	3.05	-0.95	0.00	-1.01
t-stat	-3.28	3.46	3.21	-3.33	-0.73	-3.47
XLY	-0.16	-0.05	3.21	-0.68	0.00	0.28
t-stat	-2.25	-0.21	2.26	-2.47	1.96	1.07
XLP	-0.04	0.56	1.00	-1.47	0.00	-0.20
t-stat	-1.03	2.27	0.79	-5.2	0.7	-1.71
XLB	-0.09	0.46	2.40	-0.45	0.00	-0.64
t-stat	-1.28	2.14	2.49	-1.76	-1.43	-3.6
XLK	0.06	0.02	-0.77	-0.59	0.00	0.31
t-stat	1.12	0.09	-0.86	-2.19	0.05	1.82
XLU	-0.11	1.18	1.82	-1.34	0.00	-0.57
t-stat	-1.72	4.6	1.35	-4.41	-0.86	-3.76
XLE	0.36	1.02	-4.01	-0.47	0.00	-0.95
t-stat	4.04	**4.82**	-3.1	-1.59	-5.71	-5.46
XLF	-0.09	-0.68	1.07	-0.77	0.00	0.98
t-stat	-1.66	-2.49	1.28	-2.57	4.38	4.14

allocation method. An analysis of different allocation methods is outside the scope of this paper.

The decision for the sector allocation will follow the same rules-based process at the beginning of each month. By following a set of rules, we are able to take emotion (or any other subjective factor) out of the decision-making process. This gives the best chance of being able to replicate the performance characteristics from our backtested strategy going forward. The rules are as follows:

1. On the first day of the month, calculate the independent variables for each sector using the past 12 months.
2. Plug each of these independent variables, along with the regression coefficients, into the regression formula.
3. If the result is positive, allocate 1 / 9 of the portfolio to that sector.
4. The sector rotation strategy will hold the sectors with positive regression results (future return predictions) for the entire month.

For instance, if the model results in positive values for six sectors, the strategy will invest in those six at 11.1% (approximately 1 / 9) each, for a portfolio that is 66.6% invested in equities and 33.4% invested in cash.

Table 14 contains the significant regression coefficients determined by mvreg. For example, $Return_{t+12}$(XLV) will be calculated each month using the equation

$$Return_{t+12}(XLV) = -0.67021(Drawdown_{t-12}) + 0.0003753(LinRegSlope_{t-12}) + 0.28743(EXRET_{t-12})$$

The resulting 12-month future return prediction for the Healthcare sector is a function of three of our five tested independent variables. Each sector will follow this format with its respective regression coefficients and independent variables.

Select Sector SPDR ETF Sector Rotation—Performance

The monthly return performance data presented in this section is based on the Select Sector SPDR ETF sector rotation strategy ("Strategy") outlined in the Select Sector SPDR ETF Sector Rotation—Outline section above. The Strategy's monthly returns were imported into Morningstar Direct to show performance compared to the S&P 500 Index. Performances are shown gross of fees. The in-sample date ends on 11/30/2012, performance shown after that date is out-of-sample.[9]

Table 15 gives the performance of the Strategy benchmarked to the S&P 500 for the full time period (1/1/2000–11/30/2015). On a risk adjusted return basis, as shown by the Sharpe ratio.[10] In this paper we are taking the risk-free rate to be 0., alpha[11], and beta,[12] the Strategy outperformed the S&P 500 Index. It also achieved a lower annualized standard deviation and a higher annualized return. The max drawdown and worst month are both considerably better as well.

The up capture ratio for the Strategy is 72.29%. This means that when the S&P 500 has a positive monthly return, the Strategy, on average, is up about 72% as much as the S&P 500. The down capture ratio for the Sector Rotation is 52.25%. This means that when the S&P 500 has a negative monthly return, the Strategy, on average, is down only half of the S&P 500. These two measures provide evidence that the Strategy offers protection in periods of market decline while still participating in periods of market growth.

The alpha of the Strategy over this time period is positive. An alpha of 3.43% means that the Strategy is adding value to the S&P 500 by about 3.43% per year.

The beta value for the Strategy is 0.60. Beta less than 1 indicates a strategy that is less volatile than its benchmark and beta greater than 1 means the strategy is more volatile than its benchmark. For the Strategy, we can expect the price to move with about 40% (1 – 0.60 = 0.40) of the volatility of the S&P 500, on average.

Table 14. Regression Coefficients for Calculating $Return_{t+12}$

Sector	β_0	β_1	β_2	β_3	β_4	β_5
Ind. Var.		$Return_{t-12}$	s_{t-12}	$Drawdown_{t-12}$	$LinRegSlope_{t-12}$	$EXRET_{t-12}$
XLV	0	0	0	-0.6702156	0.0003753	0.2874347
XLI	-0.1666002	0.9111505	2.227321	-1.165288	0	-0.9317845
XLY	-0.1738631	0	3.13873	-0.8249454	0.000382	0
XLP	-0.0114972	0	0	-1.519858	0	-0.2706815
XLB	-0.0494748	0.3768665	1.475752	-0.4973565	-0.0001328	-0.339808
XLK	0.3515096	-0.7801845	-4.960361	0	0	0.5636693
XLU	0	1.261372	0	-1.354802	0	-0.8863592
XLE	0.2928439	1.17492	-3.744959	-0.7553954	-0.0002774	-1.035919
XLF	-0.1212807	0	0	0	.0008231	0

Table 15. Performance Statistics 1/1/2000–11/30/2015

	Return	Stdev	Sharpe Ratio	Alpha	Beta
Sector Rotation	7.04	10.06	0.55	3.43	0.60
S&P 500 TR USD	4.19	15.17	0.23	0.00	1.00

	Up Capture	Down Capture	Max Drawdown	Worst Month	Correlation
Sector Rotation	72.29	52.25	-28.90	-11.07	0.91
S&P 500 TR USD	100.00	100.00	-50.95	-16.79	1.00

Correlation can range between -1 and +1, with +1 implying that as an asset moves up and down, the other asset moves in lockstep. The Strategy's correlation to the S&P 500 is measured at 0.91. This high correlation is achieved while this portfolio is, on average, 68% invested in the Select Sector SPDR ETFs.

Figure 2 shows a chart of the investment growth, given as a percentage, generated by the Strategy and the S&P 500 Index. This time period covers a total of 191 months. The Strategy outperformed the S&P 500 in 96 of the 191 months (50.26%) by achieving a cumulative return of 195.4% vs. the S&P 500's 92.1%. In the months where the Strategy outperforms, it does so on average by about 1.65%, and when it underperforms it does so by about 1.33%. Next, let's take a look at the performance of the Strategy over the last three years to see if the model can be verified by out-of-sample data.

Table 16 gives the performance of the Strategy benchmarked to the S&P 500 beginning 12/1/2012 and ending 11/30/2015. Over the full time period, which included several market cycles, we saw that the strategy delivered superior performance to the S&P 500 in several risk adjusted metrics. For the last three years the market has been in a low volatility, upward trend with very few drawdowns. This is a tough market environment for a trend-following approach. Yet, the Strategy still delivered positive alpha and reduced beta and maintained the same Sharpe ratio as the S&P 500. This result adds significance to our regression models, bolstering the argument that this is not a statistical fluke and that multivariate regression is able to pick up on real trends in the data.

It is important that a backtested portfolio include results that are verified by out-of-sample data (also called "forward testing"). Forward testing helps to minimize "hand-picking" the best results from the past to create a strategy that backtests favorably.

The Strategy has a higher 3-year Sharpe ratio in 47 of the 52 data points. Note, however, that Sharpe ratio as an evaluating measure comes into question when the calculated value is negative. (Israelsen, 2009) When I remove those that are negative for each of the portfolios, the Strategy has a higher (positive) Sharpe ratio in 31 of the 36 data points .

Summary

With this paper, I have shown how to identify relationships among the Select Sector SPDR ETF past performance statistics and future returns using multivariate regression analysis. I interpreted this analysis in a way so as to make it accessible to a variety of active investment practitioners.

I began with a brief explanation of the assets to be used as representation for the sectors of the S&P 500 Index, namely, the logarithmic, monthly returns of the Select Sector SPDR ETFs. I followed this explanation with a description of the input variables to be used in the multivariate regression analysis. I chose the independent variables for their logical application to how investors evaluate assets. The dependent variables were the future returns that occurred in the past.

Next, I established how these input variables interact when the length of the two time variables are adjusted. I found that this type of statistical analysis is sensitive to both the look back and future return time variables. The routine for evaluating each model's goodness of fit statistics involved first analyzing the overall model predictability, given by the F-ratio. Then, if this ratio was of significance, as measured by the p-value, I

Figure 2. Percentage Growth Chart: Sector Rotation vs. S&P 500 Index 1/1/2000–11/30/2015

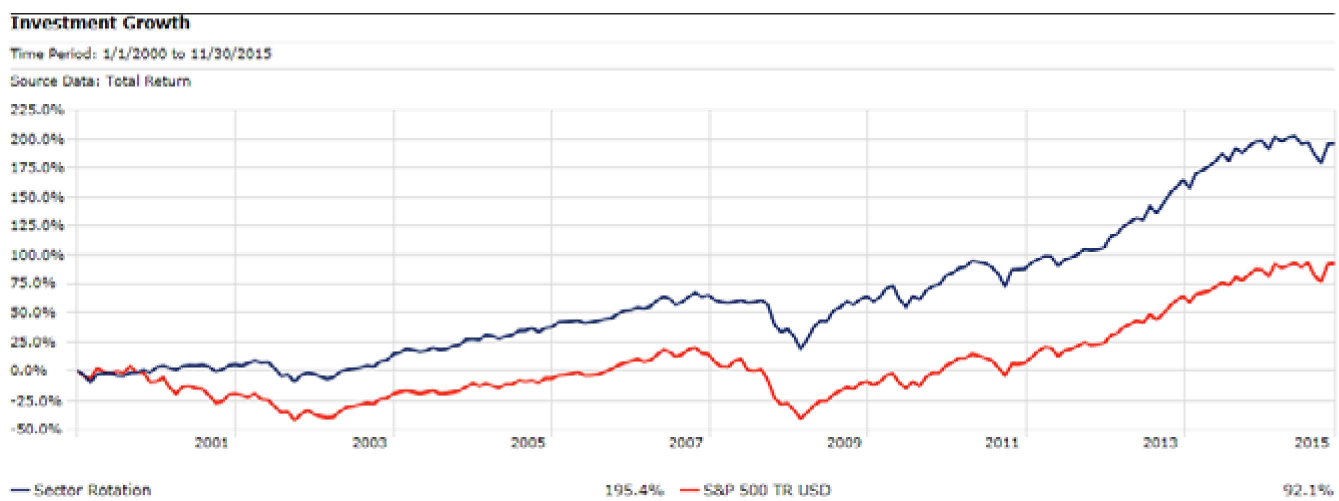


Table 16. Performance Statistics 12/1/2012–11/30/2015

	Return	Stdev	Sharpe Ratio	Alpha	Beta
Sector Rotation	13.04	8.60	1.47	0.34	0.79
S&P 500 TR USD	16.09	10.49	1.48	0.00	1.00

	Up Capture	Down Capture	Max Drawdown	Worst Month	Correlation
Sector Rotation	81.69	81.67	-7.65	-3.71	0.97
S&P 500 TR USD	100.00	100.00	-8.36	-6.03	1.00

delved deeper into the model to take a look at the regression coefficients and t-statistics of the independent variables. This made it possible to identify trends in significant variables among the different sectors.

I employed the trends identified by the analysis in an actively managed US Large Cap Equity sector rotation. The performance that resulted from this trading system beat the S&P 500 Index according to several risk adjusted performance measures, calculated both in-sample and out-of-sample. Conclusively, I have shown that a rules-based trading system, supplemented with multivariate regression, is a viable alternative to investing in a passive index. This approach is not limited to these assets, input variables, or time periods, and is merely a glimpse of the benefit that multivariate regression can provide to an active investment manager.

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Notes

[1] Monthly return rankings calculated from monthly return data provided by Morningstar from December '10 to November '15.

[2] Morningstar Direct is a cloud-based investment analysis platform that provides access to institutional quality data, analytics, and research. and span a total of nearly 17 years (1/1/1999 to 11/30/2015).

[3] Stata is a general-purpose statistical software package used for data management, statistical analysis, graphics, simulations, regression, and custom programming. mvreg (multivariate regression) command takes the independent and dependent variables for each sector at every time period and finds a straight line that best fits the data.

[4] A coefficient is a multiplicative number in an equation. For example, in $2x - 0.5y$ the coefficients of x and y are 2 and 0.5, respectively.

[5] Mean reversion is the assumption that an asset's price will tend to move to the average price over time.

[6] The intercept, or constant, value of a regression model is the mean of the dependent variable when all independent variables are set to 0.

[7] If R^2 is not adjusted, it increases with each additional independent variable included in the calculation which can mislead results.

[8] For a more detailed description of how the F-ratio and associated p-value are calculated, please refer to Winter, 2015.

[9] Out-of-sample indicates a time period that was not used in determining the regression coefficients.

[10] Sharpe-Ratio is calculated as the annualized return less the risk-free rate and then divided by the annualized standard deviation.

[11] An alpha value of 0 indicates an asset that is perfectly tracking its benchmark.

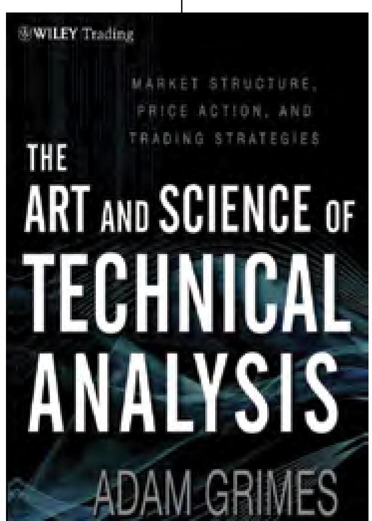
[12] Beta is an indication of how an asset's price will move in response to the benchmark.

The Art and Science of Technical Analysis—by Adam Grimes

Reviewed by Regina Meani, CFTe

My interest in the Adam Grimes tome was initially stirred by its title. In the early days of technical analysis, it was very much held as an art, as the technology required for a major progression into science was not available. If we go back roughly 30–40 years, much of technical analysis was described as "charting," and the analyst drew their charts by hand, relying on the patterns and trends that developed from the price movements, hence one of the reasons for a reference to art. Of course, some indicators were used, but these too had to be created manually and were very time consuming. The entire process of hand-drawn charts and manually created indicators needed much discipline and time. Over the years, the pendulum has swung almost completely to the science side of things; not only are our charts drawn on computer, but we are bombarded with a plethora of indicators and other technology-driven amendments. Grimes very aptly describes the relationship between the two in his preface.

> *In reality neither can exist without the other. Science must deal with the philosophical and epistemological issues of the edges of knowledge, and scientific progress depends on the inductive leaps as much as logical steps. Art rests on a foundation of tools and techniques that can and should be scientifically quantified, but it also points to another mode of knowing that stands somewhere apart from the usual procedures of logic.*[1]



What is encouraging in Grimes' style is that he does not present a rigid system that must be strictly followed, and each section of the book can be taken as a standalone and gives the reader breathing space to consider and digest his concepts and ideas. He tends to repeat some of his underlying themes; perhaps the most notable of these is the power of buying and selling pressure, which is the key driver of markets and is as relevant to all markets today as it was 30 or even 100 years ago.

There are four main parts to the book. Part One deals with concepts to give the trader an edge and offers an approach to chart reading and understanding of price patterns. There is also a section on Wyckoff, giving the reader an alternative methodology. Part Two delves more heavily into price movements and the development and transition of trading ranges and trends. Part Three takes a bigger leap into the basic underlying foundations of technical analysis by presenting detailed trading patterns in real market situations. The author also covers the use of some indicators and how to manage a position and the associated risk factors, which is essential to all traders and investors alike.

Moving on to Part Four, there is a slightly different tone, as the concentration is now pointedly focused on the individual trader and deals with the emotions and psychological issues they may face.

> *While Grimes focuses on what he terms the "self-directed" trader and the journey to profit making, he provides some interesting slants on the traditional concepts of technical analysis that the more advanced trader and investor may find insightful and interesting. As a believer that drawing your own charts can provide you with an understanding of market action that cannot be gained from a computer, Grimes stands with a group that many would call the dinosaurs of technical analysis. It rightly follows that he is a strong advocate of the art and science of technical analysis.*

> The two depend on each other: Science without Art is sterile; Art without Science is soft and incomplete. Nowhere is this truer than in the study of modern financial markets.[2]

Overall, Adam Grimes draws on a wealth of experience to present a well explained package of trading concepts aligned with technical analysis.

About the author

Adam Grimes has over 20 years of experience as a trader, analyst, and systems developer. He is currently the CIO of Waverly Advisors, an asset management and risk advisory company based in New York. Grimes started out as an individual trader in currency and agricultural futures markets before managing a private investment partnership. He also spent several years at the New York Mercantile Exchange.

Notes

[1] A Grimes, The Art and Science of Technical Analysis, John Wiley & Sons Inc, Hoboken, New Jersey, 2012, p. xiv

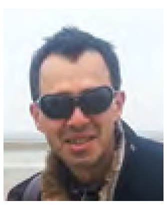
[2] ibid, p.xiv

Author Profiles

Majed Fahed Alamri, MFTA, CFTe, MSTA

Majed Fahad Alamri, MFTA, CFTe, MSTA, has been an independent technical analyst and trader since 2002. He received a Master of Financial Technical Analysis (MFTA) in 2015 and a Certified Financial Technician (CFTe) in 2013. He has also been a full member of the Society of Technical Analysts-STA (MSTA) since 2014, and he received a master's degree in education administration and planning in 2012. Mr. Alamri is the author of two books in Arabic in the field of technical analysis—one about the basics of technical analysis and another about Japanese candles. Between 2005 and 2013, he wrot e 871 daily and weekly technical reports (in Arabic) about the Saudi stock market (Tadawul), and he has been a trainer of technical analysis of the financial markets since 2008. He has also been a member of IFTA since 2006 and the Society of Technical Analysts (STA) since 2006. Currently, he is a Ph.D student in education administration and planning.

Eric Benhamou, Ph.D., CFTe, MFTA, CMT, CAIA



Dr. Eric Benhamou is currently launching Alpha Beta Performance Capital, a systematic hedge fund using medium frequency and high probability trading algos. He has a track record of successful entrepreneurship, as he previously created Pricing Partners, a complex derivatives software and evaluation startup that was acquired by Thomson Reuters. Prior to that, Dr. Benhamou served as a quantitative analyst at Goldman Sachs and Natixis. He majored in applied mathematics at the Ecole Polytechnique and holds a master's degree in statistics from ENSAE, a DEA in probability from Jussieu University, and a Ph.D. in economics from the London School of Economics. He is currently finishing a Ph.D. in mathematics at Paris University.

Constance Brown, CMT, MFTA

Constance Brown, CMT, MFTA, founded Aerodynamic Investments Inc. in 1996 (www.aeroinvest.com). She has 28 years of trading experience and managed an exclusive oil, S&P 500 and DAX futures hedge fund for six years. The fund closed up 67% in 2002, its final year. Ms. Brown's prospectus required an automatic shutdown at -20% that was never triggered. Ms. Brown advises numerous financial institutions and traders around the world and actively trades global financial futures. Seminars and lectures are an important part of showing how analysis and trading apply technical methods differently due to the demands of timing and drawdown. She continues to hold seminars in Europe and the United States. Ms. Brown has written nine books. Her second book, *Technical Analysis for the Trading Professional* (McGraw-Hill, 1999), was used for over a decade by the Market Technicians Association (MTA) as required reading for CMT Level 3. Her book *Fibonacci Analysis* (Bloomberg Press, 2009) won the Gold Medal from Axiom Business Awards and is viewed as an industry classic. She is working on a major release that will include Gann and global cash flow analysis.

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Kwun Ho Chan is a graduate of The Chinese University of Hong Kong, where he earned a B.Sc. in quantitative finance in 2012. He works as an analyst in a Hong Kong-based hedge fund and has wide experience in investment management.

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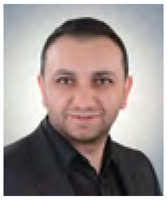
Terence Tai-Leung Chong is associate professor of economics and executive director of Lau Chor Tak Institute of Global Economics and Finance, The Chinese University of Hong Kong, and Siyuan chair professor of Nanjing University, China. He received his Ph.D. in economics from the University of Rochester in 1995. He has published over 120 articles in reputable international journals, including *Journal of Econometrics, Econometric Theory, Econometric Review, Econometrics Journal, Journal of Time Series Analysis, Journal of Banking and Finance, Financial Management, Journal of Futures Markets, Quantitative Finance, Financial Review, Pacific-Basin Finance Journal, Journal of Behavioral Finance, Southern Economic Journal, Economics Letters, Journal of Economic Psychology, Review of Income and Wealth, and China Economic Review.* He is the associate editor of Singapore Economic Review and Economics Bulletin.

King Tong Choo

King Tong Choo is a student of technical analysis and an associate member of the Society of Technical Analysts. His research interests lie in the areas of momentum and behavioural economics, which he has developed through his contribution to the Journal this year. Choo's experience includes his time in the advisory arm of EY and, more recently, his term with the economic policymaking team at the Adam Smith Institute. Choo also has a keen interest in entrepreneurship, with his latest venture being Nova Clothes, a fashion e-commerce startup.

Eng. Mohamed Elkholy, CETA, CFTe, MFTA



Eng. Mohamed Elkholy, CETA, CFTe, MFTA, is a technical analyst with 10 years of experience in the field of financial markets and is a professional automated trading systems programmer, as he served as a freelancer signal provider. He is also an expert in Metatrader 4, MQL5 and Metastock. He graduated from Mansoura University, Faculty of Engineering, and first acquired an interest in technical analysis in 2006 when he started investing his own portfolio and studying technical analysis. He has been a member of the Egyptian Society of Technical Analysis since 2008, focusing his efforts on studying financial astrology and the work of William D. Gann regarding forecasting the market movements.

Mr. Elkholy developed a theory he called "Price Rotation Around Pyramid Cones Theory," which may contribute to unveiling some of Gann's undisclosed work. The theory is a conclusion of collecting what Gann stated and developed in his books. This theory helped Mr. Elkholy to forecast price targets and determine trend strength. Additionally, by using the tenets of his own theory, he created two indicators, which he called Square of Nine Bands and Square of Nine Oscillator.

Regina Meani, CFTe

Regina Meani, CFTe, covered world markets as a technical analyst and associate director for Deutsche Bank prior to freelancing. She is an author in the area of technical analysis and is a sought after presenter both internationally and locally, lecturing for various financial bodies and universities as well as the Australian Stock Exchange. Regina is a founding member and former president of the Australian Professional Technical Analysts (APTA) and a past journal director for IFTA, carrying the CFTe designation and the Australian AMT (Accredited Market Technician). She has regular columns in the financial press and appears in other media forums. Her freelance work includes market analysis, webinars, and larger seminars; advising and training investors and traders in market psychology; CFD; and share trading and technical analysis. She is also a former director of the Australian Technical Analysts Association (ATAA) and has belonged to the Society of Technical Analysts, UK (STA) for over 30 years.

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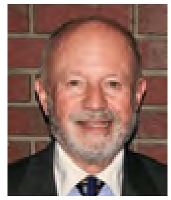
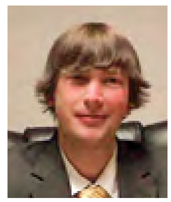


Henry ("Hank") Pruden, Ph.D., is a professor at Golden Gate University in San Francisco, California. His research interests and areas of specialization include marketing, technical market analysis, and behavioral finance. Dr. Pruden has authored numerous publications and is a member of IFTA, the Market Technicians Association, the Technical Securities Analysts Association of San Francisco, and the American Association of Professional Technical Analysts. He received a B.S. in business from California State University–Chico, an MBA from the University of California–Berkeley, and a Ph.D. from the University of Oregon.

Jordan Roy-Byrne, CMT, MFTA

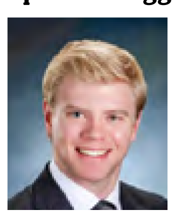


Jordan Roy-Byrne, CMT, MFTA, is the editor and publisher of TheDailyGold.com and TheDailyGold Premium, a subscriber publication that emphasizes market timing and stock selection for precious metals investors. He is a member of the Market Technicians Association and is the author of the 2015 book, *The Coming Renewal of Gold's Secular Bull Market.*

Gregory Allen Schnell, CMT, MFTA

Gregory Schnell, CMT, MFTA, is a senior technical analyst at StockCharts.com, specializing in intermarket and commodities analysis. Based in Calgary, he is a board member of the Canadian Society of Technical Analysts (CSTA) and the chairman of the CSTA Calgary chapter. He is an active member of both the Market Technicians Association (MTA) and the International Federation of Technical Analysts (IFTA). Mr. Schnell joined StockCharts.com in 2012. He currently contributes market analysis commentary to The Canadian Technician, Commodities Countdown, and Don't Ignore This Chart blogs. His primary technical interest is in the global intermarket relationships between the equities, bonds, currencies, and commodities markets. Mr. Schnell recently won two awards with the CSTA: Canadian Technical Blogger of the Year and Technical Training/Educator of the Year.

Spencer Seggebruch



Spencer Seggebruch is an investment officer at RT Jones Capital Equities Management, Inc., an SEC Registered Investment Advisor in St. Louis, Missouri. He started at RT Jones after graduating in 2013 from Southern Illinois University, Edwardsville with a degree in mathematics, specializing in actuarial science. While the majority of his coursework focused on statistical analysis, he also completed coursework in the areas of economics and finance. Mr. Seggebruch contributes to the firm in many ways but mainly researches and designs trading algorithms for use in the RT Jones Artesys managed accounts. He is currently developing new portfolio strategies founded on the principles of regression analysis. This was his first year as a competitor in the NAAIM Wagner Award white paper competition.

Prashant Shah, CMT, CFTe, MFTA

Prashant Shah, CMT, CFTe, MFTA, is a co-founder and research head at Definedge Solutions (www.definedge.com), a company that provides software, research, and training on market trading techniques. He is a trader, author, and active speaker. He started his career in 2005 and successfully headed many departments at well known financial organisations in India over the years. Mr. Shah has been practicing different forms of noiseless charting techniques and trading them across various timeframes and instruments. He is passionate about speaking, training, and writing on this subject. He regularly addresses various trading conferences, groups of investors, and trading fraternities. He also conduct courses and gives seminars on technical analysis for private and institutional investors. He keeps reading, learning, and exploring various methods of trading or analysing to bring them to noiselessness, simplicity, and objectivity. 'Keep it simple and objective' is his motto, and he firmly believes that it is an integral part of successful investing.

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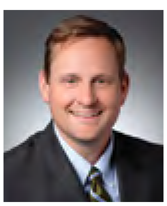

David Tonaszuck, CMT, MFTA, is an assistant vice president and market technician for LPL Financial, LLC, an independent broker–dealer. Mr. Tonaszuck is responsible for setting the technical analysis strategy across all asset classes and categories, including equities, commodities, currencies, and fixed income. He is a key member of the LPL Financial Research team's tactical asset allocation committee, which directly impacts the portfolio decision-making process. He has developed and currently manages a purely technical analysis factor portfolio for LPL Financial's Model Wealth Portfolio (MWP) platform, which is available to LPL financial advisors.

Mr. Tonaszuck has a passion for helping financial advisors maximize their profits through prudent investing and ultimately helping the end-user or retail client feel comfortable in meeting their financial goals and objectives.

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