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"Creating a new theory is not like destroying an old barn and erecting a skyscraper in its place. It is rather like climbing a mountain, gaining new and wider views, discovering unexpected connections between our starting points and its rich environment. But the point from which we started out still exists and can be seen, although it appears smaller and forms a tiny part of our broad view gained by the mastery of the obstacles on our adventurous way up."

Albert Einstein

Inside this Issue

IFTA Journal

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Letter from the Editor

by Regina Meani
STA, ATAA, APTA

What I find most exciting about the International Federation of Technical Analysts (IFTA) is its global reach. Last year as I attended the 22nd annual conference held in Chicago, USA I was struck by the theme of the event: "The International language of Technical Analysis". Over the years I have learned to appreciate the value of participating as one is almost overwhelmed by cutting edge information and research, new views and ideas on old techniques, modern interpretations of price behaviour, and much much more. But I believe even more valuable than this is IFTA's ability to bridge countries and unite cultures in a common ethos and we pay homage to this on our front cover with the reflection of the bridges across the Chicago River.

IFTA's global sweep is echoed in the journal. Inside this issue we see the return of our esteemed Professor Hank Pruden with the fourth article in his Wyckoff series. He later joins Vinodh Madhavan for a study on the implications for risk management and regulation. Other featured articles delve into market dynamics, the optimal *f* factor, Ichimoku charts and Zurab Siligadze presents us with a new indicator.

Our syllabus director, Dr Rolf Wetzer, provides us with an insightful look into the relationship between technical analysis and academia and director Julius de Kempenaer addresses the problems of asset allocation. Later in the journal, we review David Linton's book on the Ichimoku Technique and Murray Gunn's Trading Regime Analysis.

This year the John Brooks Memorial Award for outstanding achievement in the Master of Financial Technical Analysis (MFTA) has been presented to Pavlos Th Ioannou and we showcase his paper. The MFTA is the premier internationally recognised certification for technical analysis. For the candidates it represents the culmination of years of study and research with the requirement that they submit an original thesis-style research paper, applied to multiple markets.

To be considered for entry into the MFTA level, the candidates must first strive to be qualified as a Certified Financial Technician (CFTe), which requires them to complete two successive examinations in ethics, technical skills knowledge and in market behaviour and understanding.

The journal is a product of many fine contributions: to the authors I thank them for their imprint on the TA body of knowledge; to my team: Michael Samerski and Mark Brownlow for their diligent efforts in reading and editing; to director Peter Pontikis for his help and advice; to Linda Bernetich (member services manager) and to Simon Pierce at APM Graphics Management for being at the end of the line. **IFTA**

Over the years I have learned to appreciate the value of participating as one is almost overwhelmed by cutting edge information and research, new views and ideas on old techniques, modern interpretations of price behaviour, and much much more.

Regina Meani

Education and Comment

Technical Analysis in the Halls of Academia

by Rolf Wetzer

Academic interest in technical analysis started in the late 1950s. Ever since the first paper on the subject was written, researchers from universities and institutions, ... have tried to prove whether technical analysis is worthwhile ... This quarrel has not yet been solved, but for over 20 years there has been a growing body of evidence that technical analysis can be profitable...

With the 2010 IFTA conference in Berlin, the parallels between the city's history and the conflict between technical analysis and academia are remarkable. It is over 20 years since the Berlin Wall came down and East Berlin was no longer separated from the West, and it seems comparable to the gradual creaking open of the doors of academia to technical analysis.

It has been a long process of discovery by both tenets and for a long time some have likened the process to inhabitants of the moon living on its dark and light sides. While technical analysis and academic finance seem to populate the same moon, both assume that the other lives where darkness rules, unable to communicate, speaking different languages and seeming to have a love-hate relationship. As the International Federation of Technical Analysts (IFTA) is the organisation "where market technicians from around the world speak the same language", we present here some of the more recent research developments that have been conducted in the ivory towers of our academic colleagues.

Technical analysis is a very old discipline in market analysis. Created for the most part, by pure practitioners, it has been developed over the centuries from an unadulterated chart reading story into a state where many varying toolsets are used. Point & figure charts, volatility driven trading models, Elliott Wave and MESA cycle analysis are very different in nature but do have a common denominator. They use pure market data as input and therefore they are classified as technical analysis.

The body of knowledge of technical analysis has grown rapidly by borrowing from other disciplines. With the growth of computer power, technicians have integrated elements from statistics, information theory, physics, time series analysis and econometrics – just to name a few. While the toolset has become more academic and sophisticated; our intention is still driven by market returns.

Academic interest in technical analysis started in the late 1950s. Ever since the first paper on the subject was written, researchers from universities and institutions, such as central banks, have tried to prove whether technical analysis is worthwhile or whether it is just pure nonsense. For decades, the prevalent regime was the "efficient market hypothesis", i.e. the idea that market prices discount available information instantly and therefore, not only technical analysis but virtually every kind of analysis is useless. This quarrel has not yet been solved, but for over 20 years there has been a growing body of evidence that technical analysis can be profitable. Whereas technicians more often than not are only interested in the question: "Does it work?" academics prefer to ask: "Why does it work?" To answer the question, the academics use a bulk of statistical tools and explanations from behavioural sciences. Now, if you don't understand the question you won't like the answers. But at least technical practitioners could learn something from the method in which the ideas where tested and evaluated.

Maybe the very problem stems from the fact that both groups have difficulty in communicating with each other. Their language is different, their backgrounds are different, their approaches and intentions are different. Lo, Mamaysky and Wang argued, that part of the difficulties stem from linguistic barriers between technical analysts and academic finance. They give the following illustration to compare:

The presence of clearly identified support and resistance levels, coupled with a one-third retracement parameter when prices lie between them, suggests the presence of strong buying and selling opportunities in the near-term.

with

The magnitudes and decay pattern of the first twelve autocorrelations and the statistical significance of the Box-Pierce Q-statistic suggest the presence of a high-frequency predictable component in stock returns.

They concluded: "*Despite the fact that both statements have the same meaning-that past prices contain information for predicting future returns-most readers find one statement plausible and the other puzzling or, worse, offensive.*" [i]

IFTA endeavours to bridge the gap between both worlds. In the annual conferences, well-known speakers from the academic world are often invited, for example: Andrew Lo and Eugene Stanley. In the same collegial spirit, presented below is a short overview of research papers from our academic colleagues from universities and central banks. These papers have been published recently, but by no means is the set exhaustive or subjective.

One of the most comprehensive articles on the development within the empirical literature on academic technical analysis is from Park and Scott. They look at a total of 95 publications and conclude that most of the technical trading strategies discussed make money. But they found as well that despite the positive evidence on the profitability of technical trading strategies, most empirical studies are subject to various problems in their testing procedures[ii]. Another good source on technical indicators is from Taran-Morosan published in Revista Economica in 2009[iii].

In the field of chart analysis Roscoe and Howorth, also in 2009, examined chartists' decision-making techniques. They distinguished between trend-seekers and pattern-seekers. They took a more behavioural stance and argued that charting's main appeal for the user lies in its power as a heuristic device regardless of its effectiveness at generating returns[iv]. Friesen, Weller and Dunham provided a model in their 2009 work explaining the success of certain trading rules that are based on patterns in past prices. They researched "head-and-shoulders" and "double-top" patterns[v]. In 2008 Marshall, Young and Rose investigated the profitability of candlestick patterns in the U.S. equity market. Despite being used for centuries in Japan and now having a wide following among market practitioners globally, there is little research documenting its profitability or otherwise. They find that these strategies are not generally profitable. But they could not rule out the possibility that candlesticks compliment some other market timing techniques[vi]. Horton came to the same conclusion in 2009 when he examined Japanese candlestick methods for 349 stocks. He, as well, found little value in the use of candlesticks[vii].

A great deal of research has been conducted on technical indicators. Michel Fliess and Cedric Join derived two new technical indicators for trading systems and risk management. Based on trends they predict trend direction and the chance of abrupt changes[viii]. In a second paper, Fliess and Join describe how they estimate the trend via recent techniques stemming from control and signal theory[ix].

Academics seems to have a penchant for testing either moving average cross-over techniques or simple breakouts. Pavlov and Hurn applied both strategies to a cross-section of Australian stocks in 2009. The performance of the trading rules across the full range of possible parameter values is evaluated by means of an aggregate test that does not depend on the parameters of the rules. They used bootstrap simulations to verify their results[x]. Marshall, Quian and Young went on to try both techniques on US stocks during the period from 1990 to 2004. As with Pavlov and Hurn they found these rules were rarely profitable. They conclude that when a rule does produce

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statistically significant profits on a stock, those profits tend to be greater for longer decision period rules[xi]. Focusing on the sensitivity of the performance of moving averages to changes in the length of the moving averages employed, Milionis and Papanagiotou found these trading rules to have predictive power[xii]. In the Journal of Applied Financial Economics, Mizbach and Weerts explored the relationship between n-day extreme values and daily turnover. They found that turnover rises on n-day highs and lows and is an increasing function of n[xiii].

In their working papers for the Central Bank of Chile, Alfaro and Sagner provided a method to forecast one of the most popular technical indicators: the Relative Strength Index (RSI). Their method is based on the assumption that stock prices can be characterised by the standard binomial model widely used for pricing options[xiv].

Emanuele Canegrati, in his MPRA paper: *A Non-Random Walk down Canary Warf*, tested 75 of the most famous technical indicators on 40 UK stocks by performing a panel data analysis. He found robust results in demonstrating that many of the indicators were good predictors[xv]. Another and very extensive study was conducted by Valls-Pereira and Chicaroli in which they tested 26140 strategies in order to verify the existence of predictability. They selected models by variance ratio profiles with a Monte Carlo simulation. To verify the existence of positive out of sample returns, they carried out a powerful test called White's Reality Check[xvi].

Research from older publications is also very valuable. Readers with a foible for history might read the 1961 and 1964 works of Alexander[xvi, xviii] and the 1995 Federal Reserve Bank of New York report by Osler and Chang[xix]. For the Journal of Finance Lo, Mamaysky and Wang did some very extensive work in testing some classical chart patterns using objective computer-implemented algorithms[xx]. Also for the Journal of Finance, Brock, Lakonishok and LeBaron analysed 26 technical trading rules using 90 years of daily stock prices[xxi]. Another astonishing study is from Boswijk, Griffioen and Hommes who applied a large set of 5350 trend following technical trading rules to cocoa futures, finding that 72% of the trading rules generated positive returns, even when corrected for transaction and borrowing costs[xxii].

Whether one is impressed or not by the studies listed above, they show that the development within technical analysis is going to be dominated by computers and rigorous testing procedures. This trend can also be observed in non-academic journal articles or research published by brokerage houses. In asset management companies, technical approaches are sold under the label of quantitative analysis or with the stigma of behavioural finance. Different methods from other subjects will be mixed in order to create new trading rules and the author of this article believes that these trends will hold for at least some years to come and advise that readers keep an open mind to these developments in order not to find ourselves on the dark side of the moon. **IFTA**

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Education and Comment

Asset Allocation, ETFs and Technical Analysis

by Julius de Kempenaer

One of the most important questions, if not the most important, an investor needs to address is the asset allocation in a portfolio. As we all know, and have read in various academic publications, about 90% of the results of a portfolio are the result of the chosen asset allocation. Over the past few years asset allocation has become a hot topic, especially now that commercial investment companies have found out that asset allocation can be offered in the form of "overlays" or other types of products away from main stream fund management.

"Once upon a time", in my world that is about 20 years ago when I worked as a portfolio manager for Equity & Law Life insurance, investment portfolios (equities or bonds) were primarily guided on their geographical position. A fund that contained equities as well as bonds was called a mix-fund. Investments related to the assets of the insurance company were primarily driven by matching assets and liabilities. Nice bar-graphs with expected liabilities, based on actuarial (the smart guys in the next department) calculations, coming from the outstanding policies and the expected returns of the existing portfolio. When the height of the bars at any point in the future started to differ we primarily adjusted the maturity of bonds in the portfolio to get everything in line again.

It's clear that a lot has changed in that field over the past 20 years. The world, much more than in the old days, has become our playing field. We now have developed markets and emerging markets. Equity investors nowadays guide primarily on sectors, regional or global, and hardly anymore on countries. Bond investors can choose between "govvies" or "credits" both in various gradations and loan formats and obviously in various regions. Outside of traditional equities and bonds as asset classes investors can now easily diversify into commodities, real estate (direct or indirect), private equity and last but not least hedge funds… And if we have not found a formal name for some investment format we just call it "alternative investments". All these definitions, by the way, are far from universal. One investor may claim that hedge funds are part of the alternative investments space while another investor sees both as two totally different asset classes. Same goes for the naming of the process itself. We have GTAA, TAA, DSA(A), SA(A) or Global Tactical Asset Allocation, Tactical Asset Allocation, Dynamic Strategic Asset Allocation, Strategic Asset Allocation… and I probably missed some too. The good news is that the purpose of all these "products" or approaches is the same: making choices regarding asset classes and allocating monies to them. Technical analysis provides a very good framework in general and relative strength analysis (RS analysis) is the preferred tool in our arsenal to address this problem.

Making choices is one thing but implementing these choices into an investment process, i.e. portfolio construction, is something entirely different. In this regard ETFs (Exchange Traded Funds or trackers), another "innovation" that took the financial world by storm over the past five to ten years, are worth taking into account. Unless you are an institutional investor with enough assets to construct well diversified portfolios for each asset class at low costs, these can be used easily to implement your choices.

Technical analysis and especially relative strength analysis can serve as the tool to help in making asset allocation decisions. The choices can subsequently be translated into portfolios using ETFs. In other words TA can be the bridge from an asset allocation problem to portfolio construction.

Personally I like to approach an asset allocation problem from the top down. The first issue to address is which benchmark to use for the portfolio. If the goal of the

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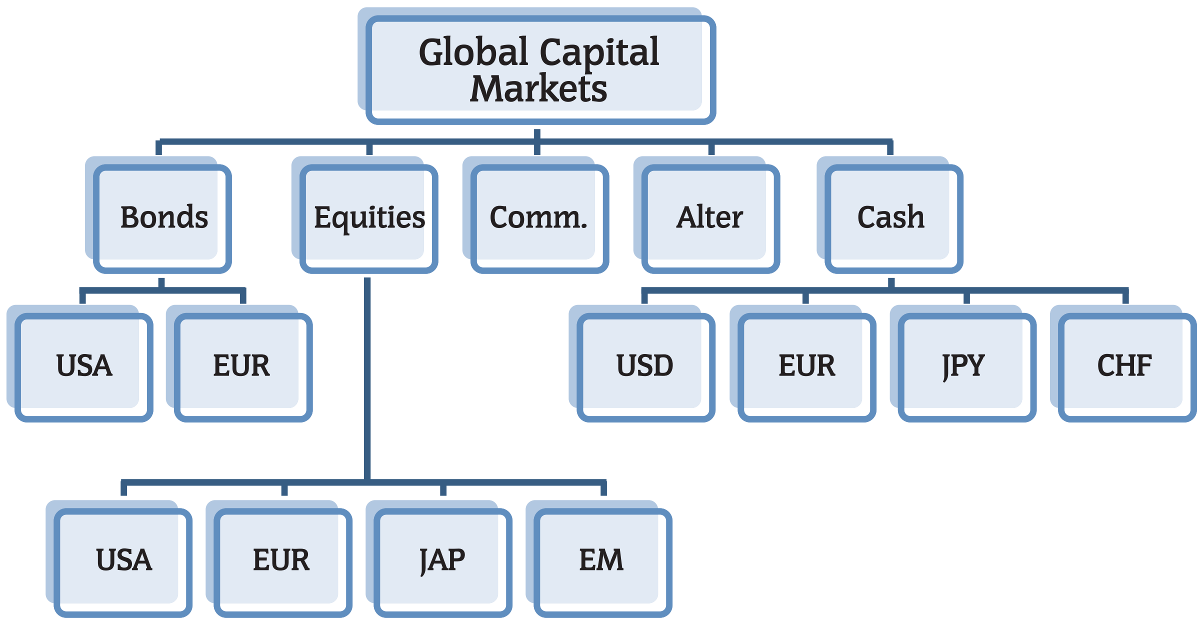

portfolio in question is absolute returns, the benchmark can be a cash index like the JP Morgan Cash Index Euro Currency three month (bb ticker: JPCAEU3M index). If the portfolio is relative return orientated one could use the MSCI Global Capital Markets index which includes a broad selection of global equity- and bond markets.

The first step is then to use relative strength analysis to determine the weights for the asset classes on the first level. For the comparison and the RS analysis it is best to use an index-series. They are usually readily available with enough history to make a useful analysis. For equities, for example, the MSCI World Index can be used as the gauge. The analysis to run would then be the MSCI world equities against MSCI Global Capital Markets, the result of that exercise will be an over- under- or neutral weighting for equities in our asset allocation. Similar analyses are then run on the other asset classes to determine the weights. It is very well possible to stop the process at this level and construct a portfolio using ETFs that cover, or come very close to, the indices used in the analysis. For equities there are multiple ETFs available that track the MSCI World Index. Also for commodities there are some options to implement a commodities allocation through one ETF. To my knowledge there is no Global Bond ETF available but a mix of two to three ETFs could create the needed exposure. For tracking hedge funds or alternative investments there are also some ETFs or ETF like products available that offer exposure to hedge fund indices.

Taking the process to the next level is also possible. This means that the indices used in comparison with the Global Capital Markets Index are now the benchmarks for the asset classes to which sub-indices will be measured. In equities for example the MSCI World Index will be the benchmark to run the RS-analyses, for example, MSCI US against MSCI World and MSCI Europe against MSCI World etc… Similar analyses will be run in the other asset classes. Again a portfolio can then be constructed using ETFs to create exposure using weights based on the RS-analyses. This decision tree can be branched out further as long as data and ETFs to create exposure are available.

A word of caution with regard to back-testing systems that are based on this concept needs to be voiced. When putting together a system for asset allocation it is very natural and understandable to use the index-data used in the RS-analysis to generate the back test results. For an initial test that's fine but when things are getting more serious, at some stage one needs to make the switch from index-data to investment index-data. My experience is that this will put a big dent in the performance as measured on index-data, especially when it concerns an actively trading system. An example is shown in Figure 1 with a back test of an asset allocation model using six asset classes, through ETFs, over a twelve year period.

Figure 1

An asset allocation back test model for six asset classes, using ETFs over a twelve year period.

The difference between the two lines is clearly defined. Over the twelve year period the divergence is around 100 points (%). The results based on index-data are very appealing, not to say very good. When switched to investment instruments the numbers drop significantly and are best described with a Dom Deluise quote: “Nice, nice, not thrilling, but nice”.[1]

The bottom line is that technical analysis (RS-analysis) can provide the necessary tools to make choices and bridge the gap from an asset allocation “problem” to an actual portfolio using ETFs. **IFTA**

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Julius de Kempenaer

Using Multiple Time Frame Clouds to increase the power of the Ichimoku Technique

by David Linton

Abstract

Technical Analysts can improve their trading results using multiple time frame clouds on their charts. Constructing multiple clouds from different time frame charts such as daily and weekly and displaying them on the same chart can provide a valuable picture of short-term and long-term support and resistance areas. Through backtest results of multiple cloud trading strategies, this paper will show the value of combining time frames on Ichimoku charts.

Introduction

The Ichimoku chart, commonly known as the Cloud Chart, is a candlestick chart containing five main elements:

- **Turning Line** – plots the midpoint of the high and low of the last nine sessions
- **Standard Line** – plots the midpoint of the high and low of the last 26 sessions
- **Cloud Span 1 or A** – plots the midpoint of the turning line and standard line shifted 26 bars forward
- **Cloud Span 2 or B** – plots the midpoint of the high and low of the last 52 sessions shifted 26 bars forward
- **The Lagging Line** – plots the price line (close) shifted back 26 bars

Interpretation

The most important aspect with Cloud Charts is how the price interacts with the cloud. Because the cloud is constructed purely from price action, price movement creates its own boundaries of resistance and support with the cloud into the future. When the price is above the cloud, the cloud will act as a support area and when the price is below the cloud, the cloud will act as a resistance area. Price action interacts with the cloud running ahead of itself on a perpetual basis providing a unique roadmap for future price behaviour. Cloud touches aren't always precise, but prices often make contact, rebound or run along the cloud edges as we see in Figure 2. Prices may interact with the outer and inner edges of the cloud.

Bullish and Bearish Zones

Cloud charts provide a useful advantage in showing whether the picture is bullish or bearish at a glance. If the price is above the cloud, the state is bullish; an uptrend, prices are going up. If the price is below the cloud it is bearish; a downtrend with prices continuing to fall.

The exception to price being above or below the cloud is when it is actually contained within the cloud itself. In this instance, the direction in which the price entered the cloud decides the trend state. If prices came into the cloud from above (this will normally be a blue cloud) the picture is still bullish. If they came into the cloud from below (likely red cloud) this is still bearish territory. This state is also a potential transition

Figure 1: **Cloud Chart of the Nikkei 225 Index with elements marked**

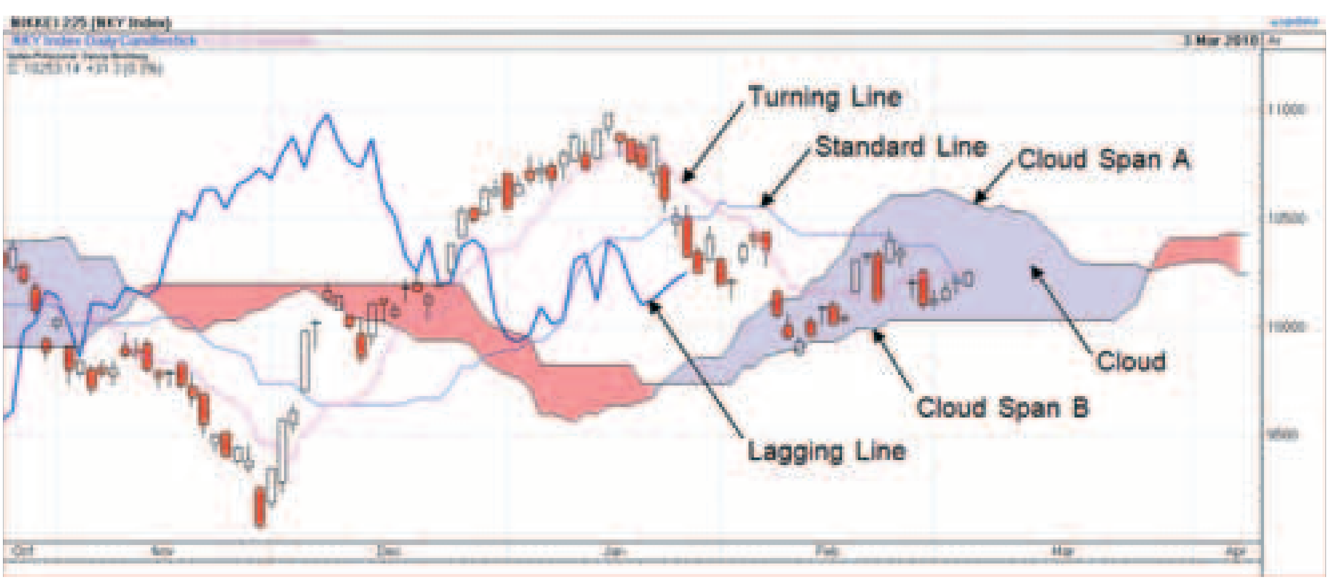
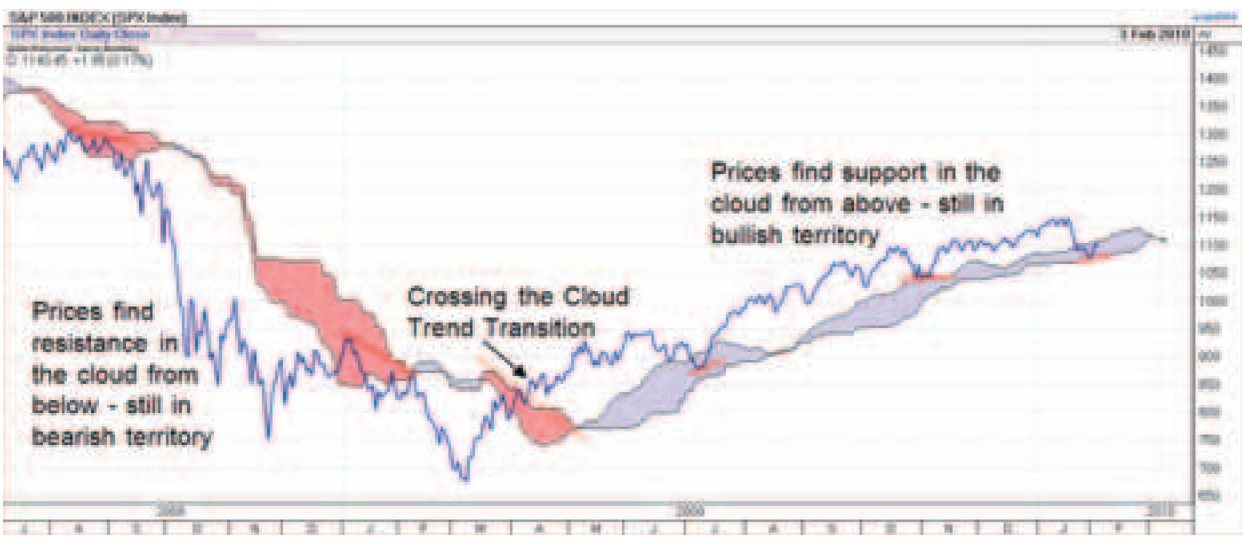


Figure 2: **British Pound against US Dollar showing price touches on the cloud**

Figure 3: **S&P 500 Index with the price testing the cloud from either side with a trend transition marked**



in trend. If the price line crosses from one side of the cloud to the other, a change in trend has occurred. This is shown in Figure 3.

The main signals

The lagging line is the price line shifted back 26 bars. This line will nearly always cross the cloud after the price, and it is the true confirming signal that the trend has changed. When this happens, especially after a long clear trend beforehand, the price will already be clearly in the new counter trend territory. Lagging line signals occur later than signals given by the price alone crossing the cloud, but false signals which are reversed soon after are much less common. Figure 4 illustrates how prices crossed the cloud more frequently than the lagging line. The lagging line made only one cloud cross at the point of transition marked with a red line on the chart.

While the lagging line will normally give more reliable signals of cloud cross than the price line, it is best to check historically whether price has interacted clearly with the cloud. The Dow Jones chart, in Figure 5, shows that the price has not crossed the cloud any more frequently than the one lagging line cross in the past couple of years. In this case more importance can be attached to a cloud cross by the price. It is worth noting the cost of the later signal here. The Dow crossed the cloud in April at 7750 points. By the time the lagging line had crossed a month later (where the price is on the x-axis) the Dow was at 8250 points.

Whether the cloud cross is read using the price or lagging line, the idea that either of them test the cloud from both sides is an important part of confirming a trend change. The idea that resistance becomes support and vice versa is well recognised in traditional technical analysis techniques. If the cloud is tested before and after the cloud cross this provides more certainty that a trend change is in progress. Figure 6 highlights several touches either side of the cloud with the New Zealand Dollar.

Figure 4: **Gold chart showing how the lagging line crosses the cloud less frequently than the price line**

Figure 5: **Dow Jones Industrial Average illustrating reliable price signals on the cloud**

Figure 6: **New Zealand Dollar against the US Dollar highlighting price and lagging line touches on the cloud**

Using clouds as a trading roadmap

Cloud Charts provide an objective definition of trend state at a glance. The bullish (uptrend) or bearish (downtrend) trend allows for a trading stance to be adjusted accordingly. Other analysis techniques may be used for trading signals with the cloud used as a filter such that long trades are taken in an uptrend with short trading signals ignored. In a downtrend, shorting opportunities would be sought. This is featured on the chart for Oil in Figure 7.

Time frame selection

The forward projection of the cloud provides an automatic time horizon on a cloud chart. The table below shows how far into the future the cloud extends for each time frame chart. For instance the cloud on a weekly chart extends approximately six months into the future. Cloud charts allow quick views on any time frame and the corresponding time horizon by simply switching the frame of the bars on the chart. A long-term view can be gained quickly by looking at the monthly cloud, then switching to a daily chart for a medium-term picture and to an hourly chart for a shorter-term view. This multi-time frame view can be conducted much more quickly with Cloud charts than with other technical techniques.

Combining Clouds on the same charts

Cloud charts enable the analyst to look up and down a time frame easily from a preferred time horizon. This can be taken a step further by exhibiting the clouds from two different time frames on the same chart. Figure 8, the daily chart for the S&P 500 Index has the weekly cloud superimposed on the chart. In this instance the picture is bearish on the daily chart, with price and lagging line below the cloud, and bullish on the weekly with the cloud providing support. The ability to look at the picture of the clouds in relation to two different time frames provides extra information in terms of longer and short-term support and resistance for the price.

Table 1
Cloud Chart time horizon with different time frame charts

	ULTRA SHORT	VERY SHORT	SHORT TERM	MEDIUM TERM	LONG TERM	VERY LONG	ULTRA LONG
Time Horizon	Minutes	Hours	Days	Weeks	Months	Years	Many Years
Chart Frame	tick/1 Min	5/10 Mins	Hourly	Daily	Weekly	Monthly	Quarterly
Cloud Extends	30 Mins	2-4 Hours	3 Days	1 Month	6 Months	2 Years	8 Years

SHORT TERM TRADER			LONG TERM INVESTOR		
SHORT	MEDIUM	LONG	SHORT	MEDIUM	LONG

Using a Signal Delay

There is some evidence to suggest that it may be more profitable to wait a number of bars before accepting a signal for either the price or the lagging line crossing the cloud. The equity curve, in Figure 9, is the result of the price crossing the cloud for the Euro. A buy signal is given at A when the price closes above the cloud, where the last 'price outside cloud position' was below the cloud. A sell signal is given at point B where the price crosses below the cloud, with the last 'price outside cloud condition' above the cloud. In this example it would have been a more profitable trading strategy to wait a few bars to see whether prices remained outside the cloud. Using a signal delay would have avoided taking these signals on what turned out to be temporary breaches.

The first trade on this chart occurred at point A. The price closed above the cloud for just one day and that was enough for the mathematical rules of such a trading system, which has no subjective capability, to go long and buy the Euro. Running the system again and

Figure 7: **West Texas Crude continuous contract showing the cloud defining a roadmap for trading**

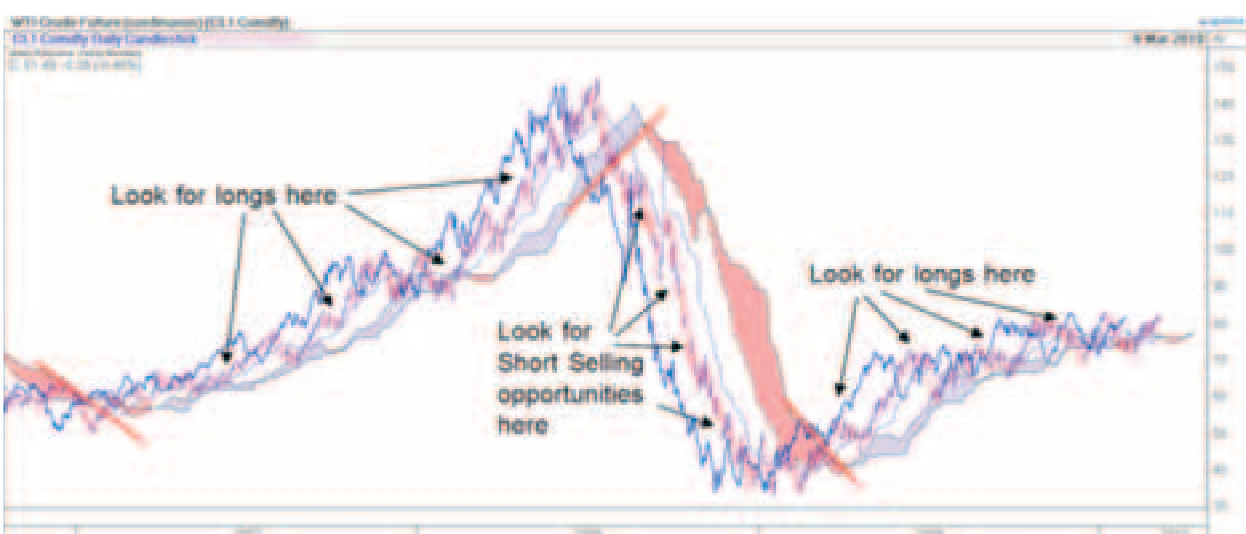


Figure 8: **S&P 500 Index with daily and weekly clouds**

Figure 9: **A signal delay would have meant temporary breaches at A and B were ignored**

Figure 10: **Using a signal delay of one day means the signals at A and B are ignored**

waiting a day, two days, and so on up to five days, the results show that waiting an extra day in this instance would have avoided the first two signals being given. In both cases at points A and B the price only closed outside the cloud for a day. In Figure 10 the drawdown in the equity line in Figure 9 has been avoided.

The same principle of using a signal delay can be applied to the lagging line crossing the cloud. Figure 11 has two temporary breaches on the lagging line at A and B, marked with vertical lines as the actual trades will occur 26 bars forward where the price is at that time.

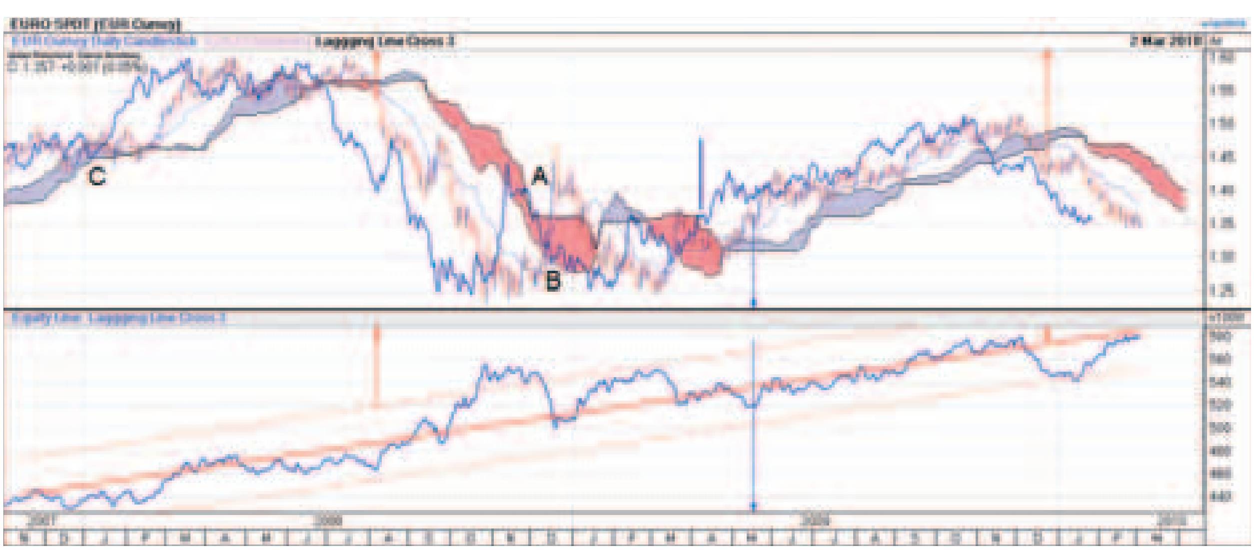
As previously shown with the price, a signal delay for the lagging line moving outside the cloud can be used to eliminate signals that are reversed soon after. Figure 12 would have optimised the signal delay by waiting three days before accepting the lagging line breach, removing the signals at A and B. Note at C the lagging line found support on the cloud in the normal way. Here the steady trend in the equity line indicates capital is growing while the underlying instrument is not trending so clearly across the test period.

This exercise can be conducted across a universe of instruments. Optimising a signal delay for the lagging line crossing the cloud, between zero and five days for the S&P 500 Index constituent stocks over a five year period for every stock and establishing which signal delay worked best produced results that were fairly evenly spread. A delay of zero days worked best for 20% of stocks, one day was best for 15%, two days for 14%, three days for 15%, four days for 15% and five days was the best signal delay for 21% of stocks. The fact that there is no preponderance towards any one signal delay period with test results evenly spread provides no clear answer for the best general signal delay to use. This highlights the subjectivity needed to properly interpret cloud charts. Previous breaches for a given instrument can provide information for the best signal delay to use.

Overall varying the signal delay can

Figure 11: **Poor signals given with temporary breaches of the lagging line moving outside the cloud**

Figure 12: **Cloud trading strategy with three day signal delay used to avoid signals at A and B**



have a big impact when deploying a cloud chart trading strategy across large universes. A test whereby signal delays on lagging line cloud crosses were optimised was conducted over five years for the top 500 US stocks. The S&P 500 Index was at 1,210 points level on March 2, 2005 and was 7.5% lower at 1,120 points on March 2, 2010. During that time the market had reached a high of 1,565 points and a low of 675 points. The strategy testing of the lagging line crossing the cloud produced an overall return of 33% over the five years for all stocks. Sixty percent of the stocks produced a profit with this strategy and forty percent lost. This goes some way to demonstrate the success of the power of the Cloud Chart technique in a falling market. If the market had been trending, this trend following technique would probably have produced even better results.

Using a longer-term cloud as a trend filter

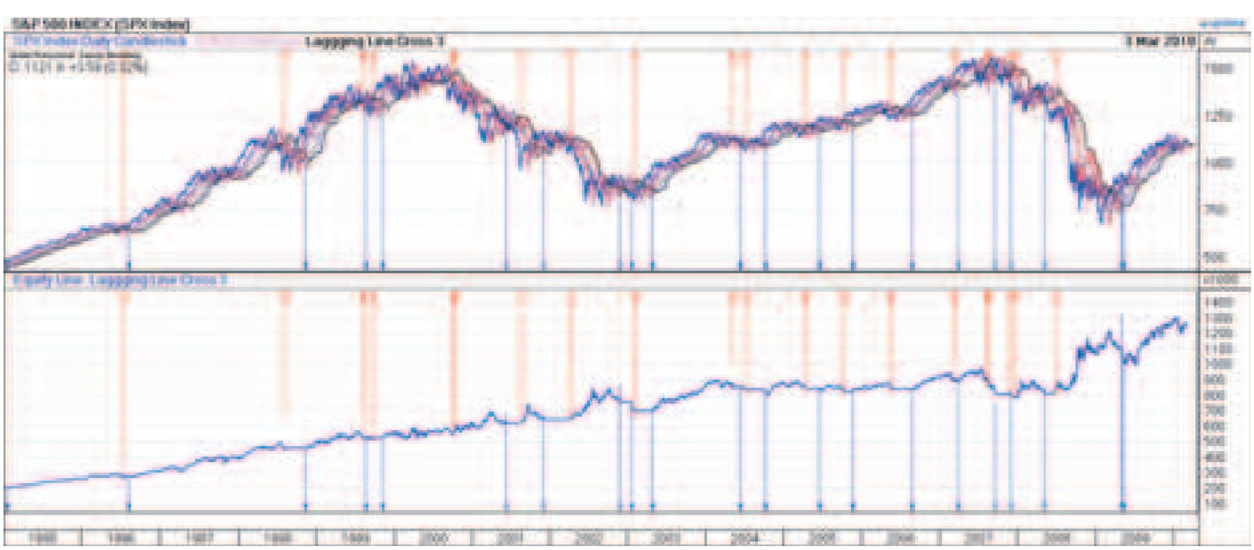
Taking a longer-term time frame cloud chart trend position into account as a trend filter can be incorporated into a cloud chart trading system by only taking trades in line with the longer-term trend. Using the weekly chart for the S&P 500 Index (Figure 13) as a roadmap: long trades (daily lagging line crossing up through the cloud) occur when the weekly lagging line is above the cloud and short trades (daily lagging line crossing below the cloud) when the weekly lagging line is below the cloud.

The trades, which follow this strategy (Figure 14), evolve with a steadily increasing equity curve over a 20 year test period. Counter weekly trend trades on the daily cloud chart were ignored purporting the trading strategy always took the longer-term weekly cloud chart trend position into account. Over the period the US stock market incresed approximately three fold, while the equity curve rose more than twelve fold.

Testing the same system for 29 currency rates found that they all made a profit over ten years. The system

Figure 13: **Weekly chart for the S&P 500 Index indicating trades to be taken on the daily cloud chart**

Figure 14: **Equity line trading the daily cloud chart taking the weekly cloud into account**



shown, with the Swedish Krona (Figure 15), whereby daily cloud signals were only taken in line with the weekly chart lagging line position, in relation to the weekly cloud. A similar trading strategy can be employed with hourly charts using the daily cloud position as their filter, or on ten minute charts with the hourly as the filter and so on.

The next step was to use the same five year test, as conducted earlier, optimising the signal delay for the S&P 500 Index constituents but this time taking the weekly cloud positions for each stock into account for the acceptance or rejection of daily signals. The results revealed that a profit was made on 430 stocks out of the 500 constituents in a sideways market over five years. Here the strategy of not taking counter-trend signals improved the number of profitable constituents from 60% to 86%. Also the overall profit result improved from 33% to a 79% return across all 500 stocks. Ignoring counter-trend signals improves trading profits dramatically.

Given the test results the effectiveness of cloud charts can be improved by viewing the longer-term cloud on a given chart. The chart of Hewlett Packard (Figure 16) depicts how the medium-term trend (daily cloud) became exhausted in early 2010 and prices having crossed through the daily cloud came back to test the base of the weekly cloud for support. Price action is frequently intersected by two clouds of different time frames providing boundaries for longer and shorter-term resistance and support ahead of the price.

Conclusion

Cloud charts are constructed with five key elements derived purely from the price. Translating the cloud ahead of the price and the lagging line 26 bars back from the price are unique aspects compared with other technical analysis techniques. Price and the lagging line will frequently interact with the cloud from either side and a trend transition occurs when the price and the lagging

Figure 15: **Daily signals on the SEK (Swedish Krona) taking the weekly chart into account**

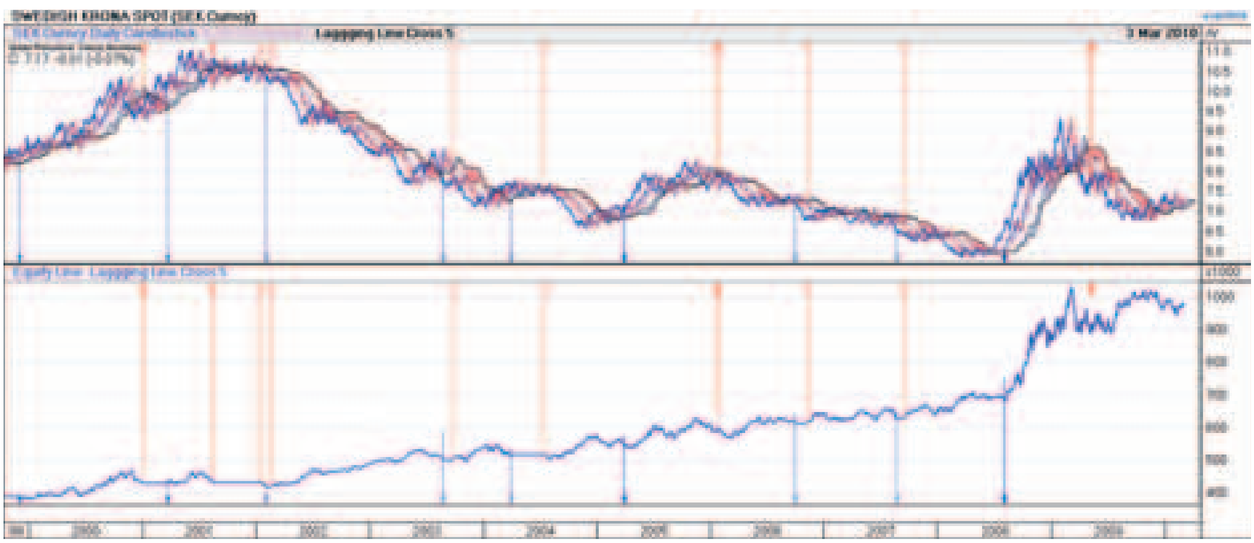


Figure 16: **Hewlett-Packard with the daily and weekly chart**

line cross the cloud from one side to the other. The lagging line crossing the cloud will normally give more reliable, but later, signals. The lagging line above the cloud means the trend is bullish and below the cloud is bearish. If the lagging line entered the cloud from above, prices are finding support and the trend is still bullish. If the lagging line entered the cloud from below, prices are finding resistance and the trend remains bearish.

Price and lagging line interaction should be studied historically to establish whether it is better to use the price or the lagging line to define trend and trend transition. The extent of temporary breaches of the cloud should also be established in order to ascertain the extent of signal delay to identify trading signals. Using a signal delay can impact trading results by rejecting trading signals that might be negated soon after a signal is given.

Cloud chart trading strategies are further improved by taking the longer-term cloud chart trend position into account for the acceptance or rejection of shorter-term cloud cross signals. The power of cloud charts can be increased by viewing two time frames together on the same chart. Tests have shown overall that the cloud chart method is a reliable analysis technique. During these tests, the construction periods were also varied to establish whether the nine, 26 and 52 periods produced the best results. There is no evidence to suggest which set of construction periods works for the best outcome with the results for different periods being widely spread. The change of the chart time frame for backtesting shorter-term, improved results more effectively than changing construction periods. Swapping the time frame of the chart will help define which time frame is giving the best results. Showing two clouds of different time frames on the same chart will increase the power of using the Ichimoku technique still further. IFTA

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Optimal *f* and the Kelly Criterion

by Ralph Vince

Abstract

Keywords: *Geometric growth optimisation, Kelly criterion, risk, gambling, markets.*

Widely-accepted in the gambling and trading community, the Kelly Criterion, named after John L. Kelly, whose 1956 Bell Labs Technical Journal paper presented the criterion resulting in wagering a constant, optimal fraction of the gambler's stake which results in maximizing the growth of the gambler's stake in the case of the gambler possessing inside information, is compared to Optimal *f*.[i]

Repeatedly in literature and commentary the notions of the Kelly Criterion and Optimal *f* are mistakenly conflated. The two are different and the former should not be used in assessing trading quantity except under certain circumstances. Optimal *f* yields the correct optimal fraction of an account to wager in all cases. This paper will attempt to distinguish the two, as well as provide means for translating between them.

The Optimal *f* calculation provides a bounded context for studying the nature of the curve whose optimal point, i.e. peak, represents the correct fraction of a stake to risk to result in the greatest geometric growth asymptotically. It is the nature of the curve whose bounding allows us to study the different phenomena of the curve, as well as provide a context from which we pursue criteria other than mere growth maximization.

Since Optimal *f* affords us this context, this paper seeks to examine another phenomenon inherent in Optimal *f*, which becomes evident when contrasted to the Kelly Criterion.

Introduction

The Kelly Criterion does not yield the Optimal Fraction to Risk in Trading Except in a Special Case

The Kelly Criterion does **not** solve for the optimal "fraction" to allocate to a trading situation except in a special case, whereas Optimal *f* does solve for the optimal fraction to risk in all cases.

Optimal *f* does **not** satisfy the Kelly Criterion (except in the special case).

The two notions are similar (their mathematical relation forthcoming) but different. To conflate the two is a mistake, and doing so in trading applications often leads to the unintended (and often dangerous) miscalculation of the quantities which one should assume so as to maximize asymptotic geometric growth.

Kelly discusses discerning fractions of a gambler's stake to risk in maximizing what is a gambling outcome, i.e. a binomial outcome (which implicitly may be extended to more than two outcomes) and he presents the required mathematics (a). In his conclusion he asserts that geometric growth is maximized by the gambler betting a **fraction** such that, 'At every bet he maximizes **the expected value of the logarithm** of his capital.'[ii]

Therein is the Kelly Criterion. The **fraction** of one's stake to bet, in order to maximize the long-run growth of one's capital, is that fraction which maximizes the expected value of the logarithm of his capital (or sum of the logs of the returns when the probability associated with each data point is the same). In other words, if we look at a stream of n returns on our capital, $A_1 \ldots A_n$, where each return is weighted by a variable, *f*, with a probability associated with each of the n returns, $P_1 .. P_n$, the expected value of the logarithm of our capital, the Objective Function in (1), is:

(1)

$$ObjectiveFunction = \sum_{i=1}^{n} \ln(1 + A_i * f) * P_i$$

According to Kelly, the value for *f* that maximizes the objective function is the fraction that results in the greatest long-run growth of capital to a gambler. Thus, the value for *f* that maximizes (1) is that value which is said to satisfy the Kelly Criterion (b).

Rather than taking the sum of the logs of the returns, we can take the product of those returns. Thus, the value for *f* that maximizes (1) will also maximize:

(1a)

$$ObjectiveFunction = \prod_{i=1}^{n} \left(1 + A_i * f\right)^{P_i}$$

Contrast this, the formula that satisfies the Kelly Criterion, with the formula for Optimal *f*, where the objective function, G, is the Geometric Mean Holding Period multiple:

(2)

$$G = \prod_{i=1}^{n} \left(1 + \frac{X_i}{\left(\frac{-W}{f}\right)} \right)^{P_i}$$

Whereas the Kelly Criterion solution uses returns, A_i, the Optimal *f* solution uses actual outcomes, X_i, based on a user-defined, consistent quantity (e.g. 100 share lot) and W is the largest losing

data point of the $X_1 \dots X_n$ data points.
$W = \min\{X_1 \dots X_n\}$.

Clearly, the Kelly Criterion when restated in terms of products (1a) so that it is compared formulaically on an apples to apples basis with Optimal *f* (2), rather than sums of logarithms (1), is not the same. They do not yield the same answers for the values that maximize them except in the special case.

The value for *f* which maximizes (1,1a,1b[r=0]) is the same as the *f* which maximizes (2) only in what is referred to herein as the "special case" in trading defined as:

1. -W = the price of the underlying instrument when purchased, **and**
2. The position to be assumed is a long position only.

When one or both of these conditions are **not** met, the Kelly Criterion (1,1a,1b[r=0]) not only results in a different value (for the optimal fraction to bet) than does the Optimal *f* solution (2), but can often result in a number that is greater than unity. This is because, as explained later, the Kelly Criterion doesn't produce an "optimal fraction to bet," but rather a leveraging factor. These numbers are identical only in the "special case."

In the more common cases, the value that solves for the Kelly Criterion is not the optimal "fraction" of a trading account to risk. In all cases, the Optimal *f* solution will yield the correct growth-optimal fraction to wager. Thus, the Optimal *f* solution is a more generalized solution of which the Kelly Criterion is a subset, applicable in trading only when both conditions of the "special case" are satisfied. When these conditions are not both met (as is typically the case in trading) one must rely on the more generalized Optimal *f* solution (2) to yield the optimal fraction to risk.

Both conditions of the special case are met in a gambling situation. In such situations, the value for *f* which maximizes (1,1a,1b[r=0]) is the same as the *f* which maximizes (2), and thus the Kelly Criterion yields the same value as the answer provided by the Optimal *f* solution.

Let us consider the ubiquitous case of a fair coin which when tossed will pay \$2 on heads and -\$1 on tails. This situation meets both criteria required for the value for *f* which maximizes (1,1a,1b[r=0]) being the same as the *f* which maximizes (2).

We find the objective function in (1) maximized where *f* = .25 wherein we have:

$$= \ln(1+2*.25) * .5 + \ln(1+-1*.25) * .5$$
$$= \ln(1.5) * .5 + \ln(.75) * .5$$
$$= .405465 * .5 + -.28768 * .5$$
$$= .202733 - .14384$$
$$= .058892$$

The expected value of the logs of returns in this case is .058892 and maximized at *f* = .25.

(Substituting (1a) for (1), we find the objective function still maximized at a value where *f*=.25.)

Similarly, solving for *f* to maximize (2) again yields an *f* value of .25:

$$= (1 + 2 / (--1 / .25))^{.5} * (1 + -1 / (--1 / .25))^{.5}$$
$$= (1 + 2 / (1 / .25))^{.5} * (1 + -1 / (1 / .25))^{.5}$$
$$= (1 + 2 / 4)^{.5} * (1 + -1 / 4)^{.5}$$
$$= (1 + .5)^{.5} * (1 + -.25)^{.5}$$
$$= 1.5^{.5} * .75^{.5}$$
$$= 1.224745 * .866025$$
$$= 1.06066$$

The result of the objective function for (2) is the geometric average return per play as a multiple. That is, it represents the multiple made on our stake, on average, each play (or compounding period) when we reinvest profits and losses.

An analog situation in trading (of the "special case" i.e., the gambling case) is that where:

1. -W = the price of the underlying instrument when purchased, **and**
2. The position to be assumed is a long position only.

We find the Kelly Criterion and Optimal *f* yield the same optimal fraction of our stake to risk(c).

This two to one coin toss gambling game is analogous to a trading situation where the price of the stock is \$1 per share and the worst-case loss is \$1 per share. The distribution of outcomes of what might happen to this trade is entirely described by the two simple scenarios. Either we exit the trade at \$2 per share or we lose the entire investment.

Now, let us consider the case where the price of the stock is \$1 per share but the most we can lose (the "worst-case outcome") is -.8 rather than −1.0. We are now faced with two possible scenarios: exit at .2 or 2.0. This is equivalent to a coin toss scenario where we either win two or lose .8.

The Kelly Criterion in this case would have us wager .375 of our stake to optimize growth in such a situation (whether using (1, 1a, 1b[r=0]) as all give the same value for f as that which optimizes each objective function).

Optimal *f*, on the other hand, has us wager .3 of our stake to maximize growth (d).

Now let us examine what happens as the size of the loss continues to shrink, from minus one, which qualifies as a "special case" where the optimal fraction determined by both methods is the same to -.1. See Table 1.

Table 1

		Optimal fractions given by:	
Heads p (.5)	**Tails p (.5)**	**(1) Kelly Criterion**	**(2) Optimal *f***
2	-1	0.25	0.25
2	-0.8	0.375	0.3
2	-0.5	0.75	0.375
2	-0.25	1.75	0.4375
2	-0.1	4.75	0.475

Notice how in all but the special case the growth optimal fractions returned by the objective functions for the Kelly Criterion and Optimal *f* are **not** the same and the values that optimize the objective functions differ. To be a "fraction" implies a number bounded at zero and one inclusively. We see here that when we deviate from the special case, the objective function of the Kelly Criterion is maximized by a value greater than one (on the last two rows) and, in all but the special case, the Kelly Criterion not only fails to yield the optimal fraction (to be demonstrated later) but doesn't even yield a fraction.

Let us assume now a three-scenario trading situation (where, for the sake of simplicity, a stock is priced at $100 per share). Since the Kelly Criterion, (1,1a,1b[r=0]), requires percentage returns as input and the more general Optimal *f* solution, (2), requires raw data points, we then have outcomes of ten, one, and minus five with corresponding probabilities of occurrence of .1, .6, and .3 respectively. We will designate these three outcomes as A, B and C, See Table 2.

Again, the values for *f* which maximize the objective functions given by the Kelly Criterion, (1,1a,1b[r=0]) versus that given by the Optimal *f* solution, (2), are disparate indeed. Note the "fraction" of one's stake to bet that maximizes the expected value of the logs of the returns, the Kelly Criterion, (1,1a,1b[r=0]), is not a fraction as the loss diminishes.

The reconciliation of the two notions, in trading, can be found by determining the relative quantities one should assume.

The Optimal *f* solution is converted into a number of "units" to trade in by dividing the largest losing outcome, W, by the optimal fraction (*f*) returned in (2), and taking this resulting quotient (herein as *f*$) as the divisor of the total equity. The individual data points used in the Optimal *f* calculation, since it is based on the raw data points as opposed to returns (as in the Kelly Criterion solution) are based on the notion of a single, user-determined, consistently-sized "unit," as is the largest losing data point, W.

(3)

$$f\$ = -W / f$$

For example, in the second row, the row where the outcome of C is minus three (corresponding to the largest losing outcome, W) with a probability of .3, we find the optimal "fraction" as determined by Optimal *f*, (2), to be 0.213519068. From this, we can solve for (3):

$f\$ = -W / f$

$f\$ = --3 / 0.2135191$

$f\$ = 3 / 0.2135191$

$f\$ = 14.0502653$

Therefore, we should capitalize each "unit" (be it one share or 100 shares or any other arbitrary but consistent, user-defined amount) by (3) in order to be at a "fraction" of our stake consistent with the *f* value used to calculate (3). In other words, when the worst-case loss manifests (outcome C in this example), where we have one unit (which experiences an outcome of minus three in this example) for every 14.0502653 in account equity, our loss will be that optimal fraction of our account, or 0.2135191:

$3 / 14.0502653 = 0.2135191$

The manifestation of the worst-case outcome is equivalent to losing a fraction, *f* of our stake in the Optimal *f* calculation, (2). Thus, Optimal *f* provides us with the fraction of our stake at risk (provided we have adequately determined the worst-case scenario) and the corresponding quantity to put on to be consistent with that fraction at risk.

Note: It is specifically because the Optimal f calculation incorporates worst-case outcomes that it is bounded between zero and one inclusively.

The Kelly Criterion solution is clearly unbounded "to the right". The disparate results given by the Kelly Criterion and Optimal *f* are reconciled through (3). If we take the price of the stock (S), or the wager (always unity, in gambling), and divide it by the quotient given in (3), we obtain the result given by the Kelly Criterion (1, 1a, 1b[r=0]):

(4)

$$\text{Kelly Criterion Solution} = S / f\$$$

Formula (4) represents not an optimal fraction to "bet" in trading, but rather a "leverage factor" to apply in trading. In other words, what we are referring to herein as the Kelly Criterion Solution is that value for *f* which maximizes (1,1a,1b[r=0]). So for the three scenario example used, and for the case where outcome C = -3, we found our *f*$, (3), to be 14.0502674. Therefore, for a stock priced at 100 (S):

$\text{Kelly Criterion Solution} = S / f\$$

$\text{Kelly Criterion Solution} = 100 / 14.05026529$

$\text{Kelly Criterion Solution} = 7.1173$

This corresponds to the value that maximizes the Kelly Criterion for this row, the fraction that maximizes the

Table 2

			Optimal fractions given by:	
A p(.1)	B p(.6)	C p(.3)	(1) Kelly Criterion	(2) Optimal *f*
10	1	-5	0.5623922	0.0281196
10	1	-3	7.1173022	0.2135191
10	1	-1	48.053266	0.4805327
10	1	-0.1	674.28384	0.6742838
10	1	-0.01	6973.8987	0.6973899

expected value of the logs of the returns. Thus, the Kelly Criterion, except in the special case, does **not** yield an optimal fraction. It is shown to be mathematically related to the optimal fraction, the fraction at risk (by (3) and (4), converting Optimal *f* to the value returned by the Kelly Criterion), but it is **neither the optimal fraction nor** even a "fraction," by definition.

Rather, the Kelly Criterion Solution, equivalent to the value for *f* which maximizes (1, 1a, 1b[r=0]), tells us how many shares to have on by virtue of the fact that it is a "leverage factor" (a.k.a. the misnomer "fraction" which satisfies the Kelly Criterion).

> **Kelly's Oversight:** *Arguably, even in the gambling situation (where W equals minus unity), the solution that satisfies the Kelly Criterion is* **not** *a fraction, appearances to the contrary, but is in fact a leverage factor and this becomes evident when we begin to move W (or, essentially in trading, -S) away from minus unity.*

Simply for any number, *f* to be zero <= *f* <= one in certain instances does not make it a fraction when it is shown that number can at times exceed one. In all such cases, *f* is a leverage factor, including the case where zero <= *f* <= one. The answer that satisfies the Kelly Criterion is not evidently what Kelly and others thought it to be, a fraction, but instead it is a leverage factor (e). *It is only in the special case that the leverage factor [as determined by the Kelly Criterion (1, 1a, 1b[r=0])] is the same value as the optimal fraction [as determined by the Optimal f calculation (2)].*

Returning to our three-scenario example, to assume a long position at $100 per share, the Kelly Criterion Solution calls to (growth) optimally lever at 7.1173022 to one. At such a factor of leverage, when the largest losing scenario manifests (minus three per unit) the resultant loss will be 7.1173022 * -3 = 21.35191. Dividing this outcome by the $100 per share gives us the resultant Optimal *f* value (2) to maximize this scenario set.

> *If one wants to consider the value that satisfies the Kelly Criterion in terms of the optimal fraction to bet or risk in trading (i.e. converting the number that maximizes the expected value of the logs of the returns to a tradable quantity to assume), one is* **de facto incorporating the largest losing outcome** *(f) (and consequently, when one utilizes the Kelly Criterion in trading, the calculation becomes contingent on the underlying price).*

The incorporation (and necessity) of the biggest loss, W, (a data point with the worst outcome of all data points being employed) is not as problematic as the reader may be inclined to regard it.

Returning to the two to one coin toss example, an instance of the special case, the optimal fraction to risk regardless of calculation method is .25.

Since the largest loss is minus one, we have an *f$* given by (3) of $4 (--1/.25 = 4), to make one bet for every $4 in our stake. Now, if we arbitrarily say that our W parameter is -$2 (leaving both scenarios the same, a loss of $1 and a gain of $2, but using a new W parameter of $2 in (2)) we find that our optimal *f* value is now .5. Then we subsequently divide the absolute value of our largest loss by the optimal *f* value, and obtain an *f$* of --2/.5 = 4. Again, we trade one unit; make one bet, for every $4 in our stake. The following table (table 3) demonstrates this for varying values of our biggest loss, W, wherein the optimal *f* for each row is determined using that row's W in (2) in determining the optimal f at that row. See Table 3.

Notice that a different largest loss, though it unbounds the solution, does not result in a different optimal quantity to assume (*f$*). The incorporation of largest loss into the objective function for Optimal *f*, (2), serves solely to bound the solution for *f* between zero and one inclusively.

It would seem then that the Kelly Criterion and Optimal *f* can be used interchangeably, and, in theory, given the translations for both, they could be. Optimal *f* is easier to employ particularly when one considers quantities in short positions and pre-leveraged positions such as futures. Further, but most importantly, a bounded solution, such as what Optimal *f* provides directly, since zero <= Optimal *f* <= one (as opposed to zero <= *f* value satisfying the Kelly Criterion < ∞), opens up a broad spectrum of possibilities.

Only in a gambling situation is the optimal fraction to wager equal to the leverage factor which satisfies the Kelly Criterion. In a trading situation, one must translate this back into the fraction dictated by Optimal *f* (unless it meets both criteria of the special case).

Most importantly, Optimal *f* is germane to the trading situation because it is bound between zero and one inclusively. Bounding permits us to:

1 Examine a bevy of geometrical relationships in context (g) and consider various points along the curve, giving these points context and meaning that an unbounded solution would not have (e.g. inflection points, *f* values as minimum expected drawdown, points x percent to the left and the right of the peak having the same return but different drawdowns, etc.). These points open up a legitimate study of the nature of the curve, the tenets of money management and position sizing.

Table 3

W	*f*	*f$*	(2)
−0.6	0.15	4	1.125
−1	0.25	4	1.125
−2	0.5	4	1.125
−5	1.25	4	1.125
−29	7.25	4	1.125

2 Combine assets into a portfolio on an apples-to-apples basis, allowing such models as the Leverage Space Portfolio Model[iii, iv] to permit us to:

3 Satisfy criteria other than mere geometric growth maximization via "Migration Paths" through this uniformly-bounded-for-all-components leverage space.

Relationship to Technical Analysis

Let us further consider point 1, specified earlier. There is a perceived point to the right of the peak where G(*f*) <1. In our two to one coin toss example, the point where G(*f*) < 1 occurs at *f* = .5. This can be seen in Figure 1.

Here we see at *f* = .5 that point where G(*f*), the average factor of growth per play on our stake, drops below 1.0. In other words, at each play, we expect to make G(*f*) * our current stake. If G(*f*) therefore is less than one, we expect at such levels of quantity to be multiplying our stake by a value less than one. In such cases, we expect our stake to diminish with each play, and approach zero. We go broke at such levels.

Employing (3), we find that at *f* = .5:

$$f\$ = --1/.5 = 2$$

Thus, *f* = .5 corresponds to making a $1 wager for every $2 in our stake. We are not borrowing to assume these wagers, we have ample funds in our stake to cover the wager (i.e. this is not a margin account, or leveraged in any manner). Note that even with an edge wildly in our favour as in this two to one coin toss, we can unwittingly bet in a manner aggressive enough to insure our demise as we continue to trade without being so aggressive that we must borrow.

Market analysis is a discipline that seeks to find the edge. Through the study of price, volume, and other data, we seek those circumstances that provide us an edge.

However, whenever we assume a position, whenever we take on a trade, we are ineluctably at some level for *f*, and are somewhere on the function G(f) at a coordinate between *f* = zero and one inclusively. We can therefore find advantageous trading situations via technical analysis but sabotage our efforts by misappropriating quantity whether we acknowledge it or not.

It is precisely these kinds of unforeseen pitfalls that make the study of market analysis - timing and selection - subordinate to this material(h).

Singularities and Discontinuities in Geometric Growth

As a discipline in its own right, the study of this material necessitates its known precepts be catalogued.

Alluding again to point 1 above, the bounded solution, (2), permits us to *examine a bevy of geometrical relationships in context and consider various points along the curve.*

Here we will add to this sub-discipline with yet another phenomenon that comports with the differences between the Kelly Criterion and Optimal *f*.

A negative expectation set of data points has no optimal fraction to bet. If the expected value of the data points is negative, we assume *f* = zero (i.e. do not wager anything so as to "maximize" growth).

Similarly, if all data points are positive (i.e. no losing data points) we have no possibility of loss at any play, and thus, in order to maximize growth, we wager 100% of our stake on each play (*f* = 1.0).

But a peculiar thing happens. We would expect that when we further diminish the loss in our two to one coin toss game, our value for Optimal *f* approaches 1.0. But this does **not** occur, as shown in Table 4.

Notice that instead of approaching 1.0 for the optimal fraction to wager, we approach .5

Let us look at the three-scenario situation mentioned earlier, in Table 5, wherein we will further diminish loss.

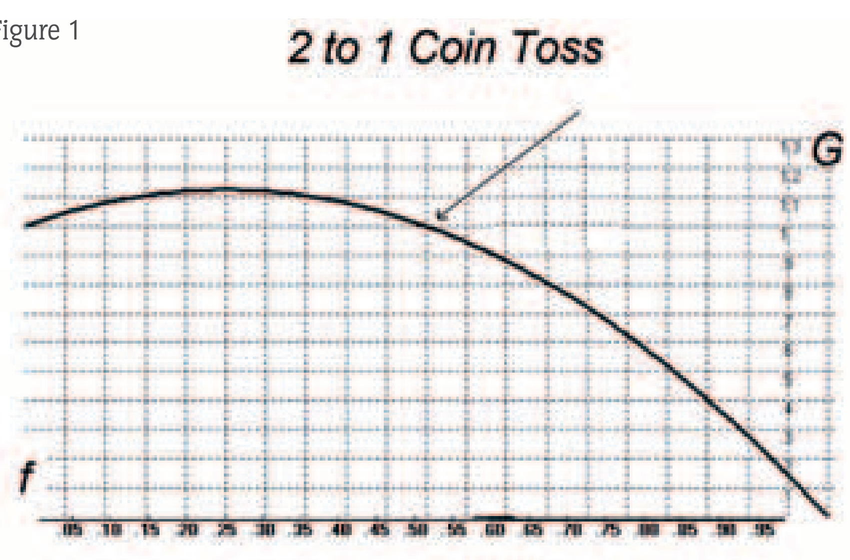
Yet again, we approach a singularity for the value for Optimal *f*, rather than approach 1.0.

Unequivocally, however, when there are no losses, growth is maximized by risking 100% of our stake (*f* = 1.0). Yet we find that as loss diminishes and approaches zero, the value for *f* approaches a **singularity**, and this singularity is less than 1.0. We see the value for *f* emerge again at 1.0 when all losses disappear, resulting in a **discontinuity**. Therefore, as loss approaches zero, the **optimal fraction** to wager approaches a singularity(i).

This seemingly unusual phenomenon is explained when we consider that Optimal *f* is bounded. If we convert to its unbounded analog, the Kelly Criterion solution (the "leverage factor" given by (1, 1a, 1b[r=0]) as *f* therein, to maximize (1, 1a, 1b[r=0])), it is clarified.

Equation (5) allows us to convert from the answer for the leverage factor given by the Kelly Criterion solution(1,1a,1b[r=0]), to the optimal fraction as determined by the Optimal *f* means, (2) as:

Figure 1



(5)

$$\text{Optimal f} = (\text{Kelly Criterion Solution} * -W) / S$$

Table 4

Heads p(.5)	**Tails p(.5)**	**Optimal *f***
2	-1	0.25
2	-0.8	0.3
2	-0.5	0.375
2	-0.25	0.4375
2	-0.1	0.475
2	-0.001	0.49974999844375100000
2	-0.0001	0.49997499938974100000
2	-0.00001	0.49999749899514000000
2	-0.000001	0.49999974853450900000
2	-0.0000001	0.49999974853450900000
2	-0.00000001	0.49999974853450900000 ‹singularity›
‹discontinuity›		
2	0	1.0

Table 5

A p(.1)	**B p(.6)**	**C p(.3)**	**Optimal *f***
10	1	-5	0.0281196
10	1	-3	0.2135191
10	1	-1	0.4805327
10	1	-0.1	0.6742838
10	1	-0.01	0.6973899
10	1	-0.001	0.69973849290211600000
10	1	-0.0001	0.69997373914116300000
10	1	-0.00001	0.69999726369202300000
10	1	-0.000001	0.69999961737115700000
10	1	-0.0000001	0.69999985261339300000
10	1	-0.00000001	0.69999985261339300000
10	1	-0.000000001	0.69999985261339300000 ‹singularity›
‹discontinuity›			
10	1	0	1.0

Because *f* is bounded to the left, at zero, by either the Kelly Criterion calculations or the Optimal *f* method, we find there is no singularity left of the peak, but only to the right, where the unbounding occurs.

The Kelly Criterion solution approaches infinity at a rate where W diminishes and S remains constant in (5), providing the Optimal *f* solution to approach a singular value.

The singularity makes sense when, for example, we consider the case in our two to one coin toss of 2, -0.00000001. At such small loss, our answer for (3) would be so high (*f$* = --.00000001 / .49999974853450900000 or make one bet for every .00000002000001005862 in our stake!) as to result in a percentage loss to our stake equal to the singularity itself (j). In other words, it is the Optimal *f*, as given by (2), that truly is the percentage, the fraction, of our stake at risk (i.e. betting one unit for every .00000002000001005862 in our stake results in a percentage loss of the singularity as a percent, or .49999974853450900000 of the stake, when the loss of , -.00000001 manifests).

As it happens, the singularity in near-lossless Optimal *f* scenario sets occurs at *f* = 1 − the probability of the losing scenario.

Conclusions

The above findings have important implications for a trader wishing to implement Optimal *f* in his future trading. One of the major impediments to implementing the usage of Optimal *f* for geometric growth in trading is the lack of knowledge as to where the optimal point will be in the future.

Since the Optimal *f* case will necessarily bound the future optimal point between zero and p (the sum of the probabilities of the winning scenarios), the trader need only perceive what p will be in the future. From there, trading a value for *f* of p/2 will minimize the cost of missing the peak of the Optimal *f* curve in the future.

This occurs because each point along the Optimal *f* curve varies with the increase in the number of plays (time), T, as G^T, where G is the geometric mean holding period multiple as given in Equation (2). Thus, at T=2, the price paid for being at any future *f* value other than the optimal value is squared, at T=3, the penalty is cubed. Just as with the measure of statistical variance, outliers cost proportionally more. Although the trader cannot judge what will be the future value for Optimal *f*, by using the value of p/2 as the future estimate of the Optimal *f*, the trader minimizes this cost and is able to make a "best guess" estimate of what the future value for Optimal *f* will be.

Note that the trader uses a predicted value for p in determining his future "best guess" for *f* . The *greatest* amount the trader *might* miss actually is the optimal point in the future and is the greater of p/2 or what we call p', which is what p actually comes in as in the future window, p' - p/2. These extreme cases manifest when the trader opts for *f* = p/2 and the future Optimal *f*=0, or, the trader opts for *f* = p/2 and the future Optimal *f*=p'. Thus, the greatest outlier, when the trader is opting to use a "best guess" for his future Optimal *f* = p /2 is minimized as the greater of p/2 and p'-p/2.

Because the Kelly Criterion Solution is unbounded to the right, we are not afforded this outcome unless, we convert it to its Optimal *f* analog.

At no losses, the Kelly Criterion solution is infinitely high, and only by convention can we conclude that the corresponding Optimal *f* is 1.0. The point of singularity we witness in Optimal *f* is mathematical, the discontinuity, by convention. **IFTA**

Notes

(a) Whether known by Kelly or not, the notion of a variable as the regulator which will maximize geometric growth was first introduced by Daniel Bernoulli in 1738[v]. It is also likely that Bernoulli was not the originator of the idea, either. Bernoulli's 1738 paper was translated into English in 1954, two years before Kelly's paper. In fairness to Kelly, his paper was presented as a solution to a technological problem that did not exist in Daniel Bernoulli's day. Further in fairness to Kelly, he never presented his criterion as being optimal in a trading context. This fallacy has been perpetuated by others. Kelly discusses the gambling context, and hence the largest loss is always −1, and hence the optimal value, *f*, is always a "fraction," 0 <= *f* <= 1. The differences, however subtle, between gambling and trading render the Kelly Criterion inapplicable in determining growth optimal quantities to risk in trading except in the special case.

(b) Vince[vi] and independently Thorp[vii] provide a solution that satisfies the Kelly Criterion for the continuous finance case, often quoted in the financial community to the effect that "*f* should equal the expected excess return of the strategy divided by the expected variance of the excess return:"

(1b)

$$f = (m-r) / s^2$$

where m=return (an expected value of return), r= the so-called risk-free rate, and s=the standard deviation in the expected excess returns comprising (m-r). It should be noted that when r=0, all three forms for satisfying the Kelly Criterion, (1,1a,1b[r=0]), will yield the same value for *f*.

(c) Regardless of the means used to determine the optimal fraction, whether by the Kelly Criterion in the special case, or the Optimal *f* means in all cases, the optimal fraction returned is never really optimal as noted by Samuelson in 1971[viii]. Rather, it is optimal in the long run sense, i.e. as the number of plays approach infinity; the optimal fraction approaches what we deem as this optimal fraction. For a single play, the expected growth is optimized for a positive expectancy game by betting 100% of the stake (optimal fraction =1.0). As the number of plays increase, the optimal fraction approaches that amount deemed the optimal fraction asymptotically, never really reaching the optimal fraction and thus the optimal fraction is actually always sub-optimal; the real optimal fraction will always be a more aggressive risk posture than that deemed as the optimal fraction.

(d) Mathematical proof of Optimal *f* providing for geometric growth optimality.[ix, x]

(e) To see this, consider Table 1, row 3, where the player wins two or loses -.5 with probability .5 each. The optimal fraction to wager is .375, whereas the Kelly Criterion solution is .75. If the player uses .75 as a leverage factor, he will be growth optimal. However, if he uses .75 as the fraction of his stake to risk, he will be far too aggressive – well beyond that which is growth optimal, and will go broke with certainty as he continues to play.

(f) Which is why the Kelly Criterion calculation of maximizing the expected values of the logs of the returns, [1, 1a,1b [r=0]) is applicable only when considering long positions. The largest loss is assumed to be the value of the position itself. To apply it equally to short positions, assumes that the worst-case outcome is a doubling of price. Thus in our three scenario example the Kelly Criterion makes the assumption that the worst that can happen is that the stock goes to 200 per share on our short position.

(g) The same mathematical relations hold in an "unbounded to the right" situation such as that provided by the Kelly Criterion Solution, but context becomes ambiguous if not lost altogether, akin to a map without a distance scale. Each separate set of data points providing a curve between zero and some ambiguous point to the right. When we get into N+1 dimensional space, where N is the number of components considered in a portfolio, each component, thus each axis, has a different scale. Opting for a messy, nearly-untenable solution such as this wherein we opt for the Kelly Criterion as opposed to Optimal *f* gains us nothing; the Kelly Criterion, in real-world applicability to trading still utilizes the largest losing data point *de facto*. Nothing is gained by opting for the messier solution it entails over the Optimal *f* solution.

(h) Particularly when the inputs to this discipline of position sizing and money management are exactly the very inputs used by the analyst; the data points used as inputs to (2), the "scenarios," are essentially the distribution of price transformed by the analyst's trading rules.

(i) This is a serendipitous phenomenon for the investor. Typically, one pays a steep price when one attempts to be at the growth optimal point in the future, and finds oneself having missed it as a result of market characteristics having changed when applying the optimal allocation versus market characteristics from which the optimal allocation was derived. There is a small range of possible values for the future optimal point. Rather than being bound zero <= Optimal *f* <= 1.0 it is rather bound between zero <= Optimal *f* <= a singularity and that singularity < 1.0.

(j) The objective function solution to the Optimal *f* calculation provides not only the geometric growth multiple per play, but the value for *f* itself dictates the percentage loss on the stake when W manifests.

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The Wyckoff Method Applied in 2009: A Case Study of the US Stock Market

by Hank Pruden

A test of Wyckoff point-and-figure projections first appeared in the 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 Dow Jones Industrial Average (DJIA). In the 2009 case study we present a continuation of the real-time tests of the Wyckoff Method from both the 2004 and 2008 studies.

In the 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 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 upon the top pattern that formed in the DJIA during 2007 and the subsequent decline into 2009, there nevertheless appeared a study after the fact. 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, the student's study revealed that a point and figure count of the S&P 500 in 2009 gave an accurate forecast of the 2009 price low, (please see Appendix no.1 by Mr Brad Brenneise for fuller details of that backtesting study).

A companion article that fitted into the Wyckoff series appeared in the Journal in 2010. The article, "Wyckoff Proofs", elaborated upon the concept of "market test" that occupied an important role in those studies of the Wyckoff Method. The 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 fourth article in the series, harkens back to the first article published in 2004. Like the first article, which under-took to study the 2002-03 accumulation base in the DJIA with emphasis upon the point and figure chart projection to 14,400, this article is another study of a base in a similar vein. The article undertakes an examination of the 2008-09 accumulation base in the Dow Industrial Average and emphasis is once again placed upon the Law of Cause and Effect and the point and figure price projections for the DJIA with a forecast and a re-cap of Mr Richard D. Wyckoff methods, principally the Wyckoff Laws and the Wyckoff Tests.

Schematics for an accumulation base including places along the base to take a long position will be laid out alongside the classic Wyckoff nine Buying Tests. Considerable attention shall be focused upon the bar and figure charts of the Dow Industrial Average that generate price projections from the 2008-09 base to render the expected extent of the markup phase of the 2009-? bull-market.

Richard D. Wyckoff and his market Investment Theory

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 trading in the early 20th Century.

He codified the best practices of legendary traders such as Jesse Livermore and others, 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 which 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. The ticker tape revealed price, volume and time relationships that were advantageously captured by charts.

Comparing waves of buying versus waves of selling on the bar chart revealed the growing strength of demand or supply. With the aid of schematics of accumulation or distribution, the speculator is empowered to make informed decisions about the present position and probable future trend of a market. The figure chart is then added to project the probable extent of a price movement.

Wyckoff also revealed how to interpret the intentions of the major interests that shape the destiny of stocks and how to follow in the footsteps of those sponsors at the culmination of bullish or bearish trading ranges.

Figure 1

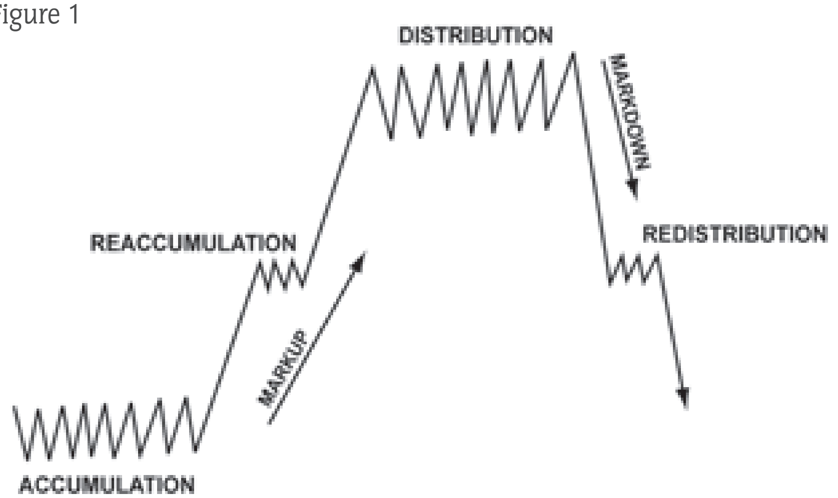


Table 1
WYCKOFF LAWS

1. **The Law of Supply and Demand** – states that when demand is greater than supply, prices will rise, and when supply is greater than demand, prices will fall. Here the analyst studies the relationship between supply versus demand using price and volume over time as found on a bar chart.
2. **The Law of Effort versus Results** – divergences and disharmonies between volume and price often presage a change in the direction of the price trend. The Wyckoff "Optimism versus Pessimism" index is an on-balanced-volume type indicator helpful for identifying accumulation versus distribution and gauging effort.
3. **The Law of Cause and Effect** – postulates that in order to have an effect you must first have a cause and that effect will be in proportion to the cause. This law's operation can be seen working as the force of accumulation or distribution within a trading range, working itself out in the subsequent move out of that trading range. Point and figure chart counts can be used to measure this cause and project the extent of its effect.

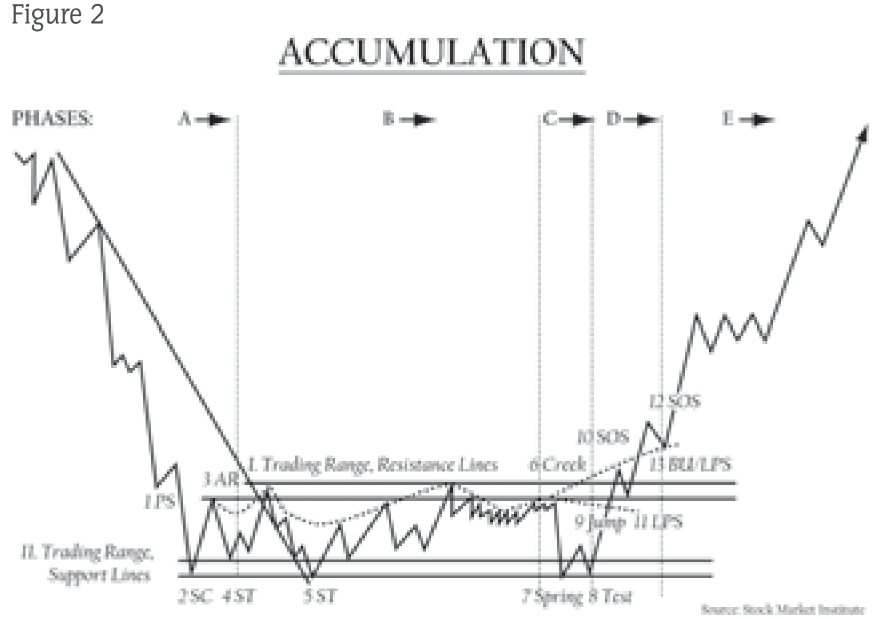
Wyckoff Schematics of Accumulation

The Wyckoff Method empowers the trader-analyst with a balanced, whole-brained approach to technical analysis decision making. The Wyckoff schematics provide picture diagrams as a right-brained tool to complement the left-brained analytical checklists furnished by the Wyckoff three laws and nine tests.

This section of the article presents the sequence of three schematics that help to demonstrate the Wyckoff Method of technical analysis. With each schematic appear alphabetical and numerical annotations that define Wyckoff's key phases and junctures found during the evolution of accumulation into the mark up phase. Several of these annotations reflect the contribution of Mr Robert G. Evans, who carried on the teaching of the Wyckoff Method after the death of Mr Wyckoff in 1934. Mr Evans, a creative teacher, was a master at explaining Wyckoff principles via analogies.

One objective of the Wyckoff method of technical analysis is to enhance market timing or when to enter a speculative position in anticipation of a coming up-move. These high reward/low risk entries typically occur around the culmination of sideways trading ranges. Trading ranges (TRs) are phases where the previous move has been halted and there is relative equilibrium between supply and demand. It is here within the TR that a campaign of accumulation is conducted by the strong hands, the smart money, and the composite man in preparation for the coming bull or bear trend. It is this force of accumulation that can be said to build a cause that unfolds in the subsequent uptrend. The building up of the necessary force takes time, and because during this period the price action is well-defined, TRs can also present favourable short-term trading opportunities with potentially very favourable reward/risk parameters for nimble traders. Nevertheless, the Wyckoff Method contends that reward comes more easily and consistently with participation in the trend that emerges from the trading range.

Figure 2



The Schematic of Accumulation in Figure 2 provides an idealised visual representation of the Wyckoff market action typically found within a TR of accumulation. While this idealised Wyckoff model for accumulation is not a schematic for all the possible variations within the anatomy of a TR, it does provide the important Wyckoff principles that are evident in an area of accumulation. It also shows the key phases used to guide our analysis from the beginning of the TR with a selling climax, through building a cause until the taking of a speculative long position.

Phases A through E in the trading range are defined below. Lines A and B define support of the trading range, while lines C and D define resistance. The abbreviations appearing on the Schematic indicate Wyckoff principles and they are also defined below:

Phases in Accumulation Schematic and their Functions

- **Phase A:** To stop a downward trend either permanently or temporarily
- **Phase B:** To build a cause within the trading range for the next effect and trend
- **Phase C:** Smart money "tests" the market along the lower and/or the upper boundaries of the trading range. Here one observes "springs" and/or "jumps" and "backups"
- **Phase D**: Defines the "line of least resistance" with the passage of the nine buying tests
- **Phase E:** The mark up or the upward trending phase unfolds

Annotations in the Accumulation Schematic Defined

1. PS – preliminary support, where substantial buying begins to provide pronounced support after a prolonged down-move. Volume and the price spread widen and provide a signal that the down-move may be approaching its end.

2. SC – selling climax, the point at which widening spread and selling pressure usually climaxes and heavy or panicky selling by the public is being absorbed by larger professional interests at prices near the bottom. At the low, the climax helps to define the lower level of the trading range.

3. AR – automatic rally, where selling pressure has been exhausted. A wave of buying can now easily push up prices, which is further fuelled by short covering. The high of this rally will help define the top of the trading range.

4+5. ST – secondary test, price revisits the area of the selling climax to test the supply/demand at these price levels. If a bottom is to be confirmed, significant supply should not resurface, and volume and price spread should be significantly diminished as the market approaches support in the area of the SC.

6. The **"Creek"** is a wavy line of resistance drawn loosely across rally peaks within the trading range. There are minor lines of resistance and a more significant "creek" of supply that will have to be crossed before the market's journey can continue onward and upward.

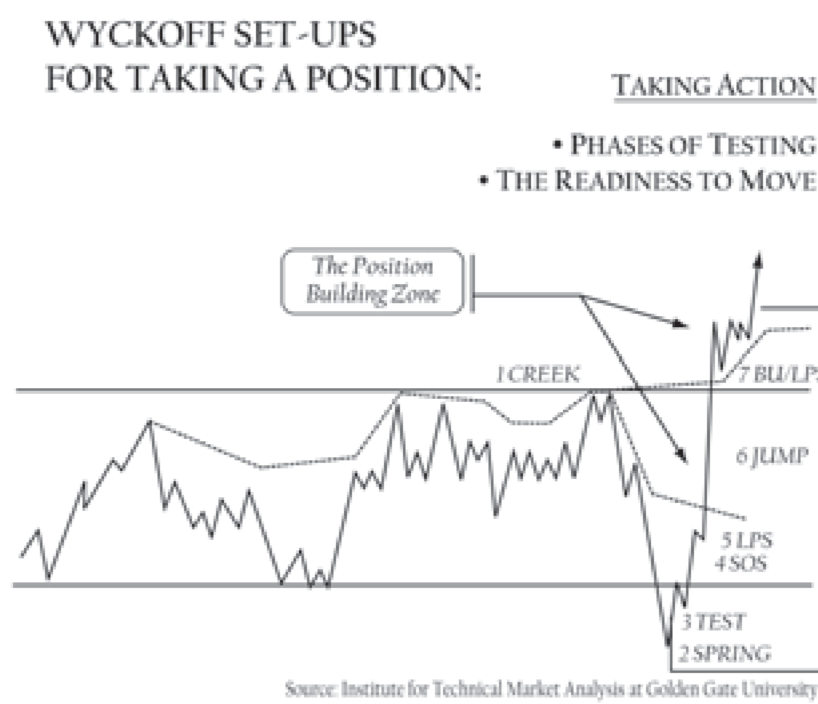
7+8. "Springs" or **"shakeouts"** usually occur late within the trading range and allow the dominant players to make a definitive test of available supply before a markup campaign will unfold. If the amount of supply that surfaces on a break of support is very light (low volume), it will be an indication that the way is clear for a sustained advance. Heavy supply here usually means a renewed decline. Moderate volume here may mean more testing of support and a time to proceed with caution. The spring or shakeout also serves the purpose of providing dominant interests with additional supply from weak holders at low prices.

9. "Jump" – continuing the creek analogy, the point at which price jumps through the resistance line; a bullish sign if the jump is achieved with increasing speed and volume.

10-12. SOS – sign of strength, an advance on increasing spread and volume, usually over some level of resistance

11-13. BU/LPS – last point of support, the ending point of a reaction or pullback at which support was met. Backing up to an LPS means a pullback to support that was formerly resistance, on diminished spread and volume after an SOS. This is a good place to initiate long positions or to add to profitable ones.

Figure 3



Whereas the three Wyckoff laws give a broader, big-picture approach to the Wyckoff method's study of charts, the nine tests are a set of principles that are more narrow and specific in their applications. The Wyckoff tests logically follow as the succeeding step to the Wyckoff laws

The Nine Buying Tests are important for defining when a trading range is finally coming to its end and a new uptrend (markup) is commencing. In other words, the nine tests define the line of least resistance in the market.

The nine classic buying tests in Table 2 define the emergence of a new bull trend out of a base that forms after a significant price decline.

Table 2: **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), 87.

Figure 4

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 4 and 5 show the bar chart and the point and figure charts of the Dow Industrial Average 2008-2009.

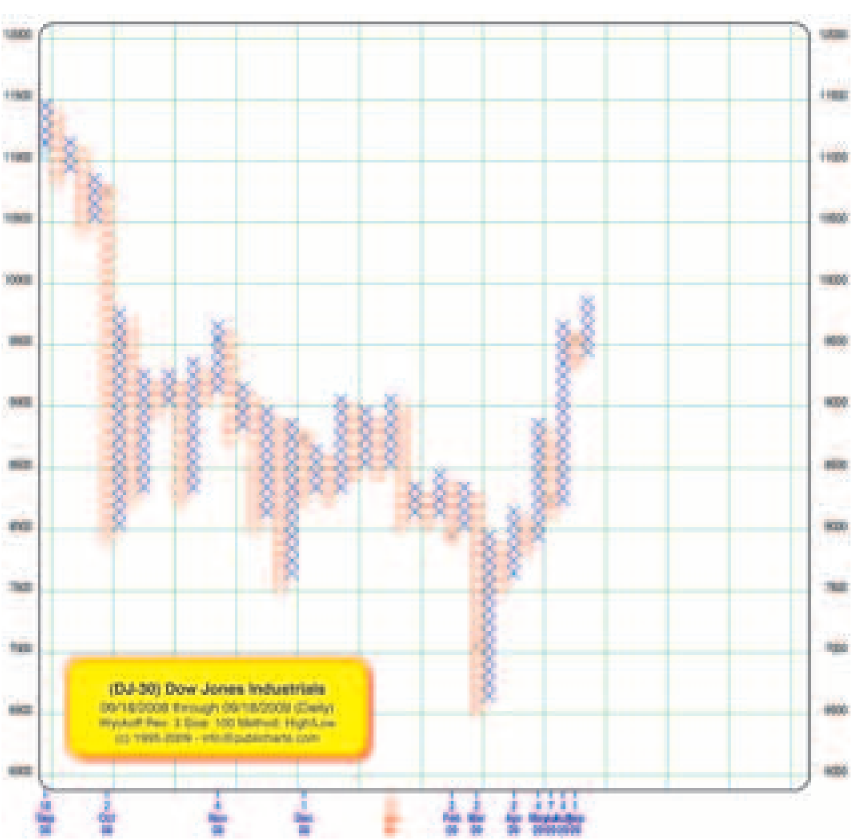
The reader is encouraged to use this application as a learning exercise. The laws of the supply and demand can be seen operating on the weekly bar chart of the Dow Industrials (Figure 4). A definition of the uptrend, the line-of-least resistance was revealed at around the 8,100 level for the Dow. At that point the Wyckoff analysts could conclude that the nine buying tests found on Table 2 had been passed. Therefore, the expectation was for a bull market to unfold. At that same juncture of 8,100 a last point of support (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 5) to apply the Law of Cause and Effect and to make upside price projections.

By counting from right to left along the 8,100 level the analyst finds 37 columns. Since this is a 3 box reversal chart, with each box worth 100 Dow points, the count becomes 37 x 300 = 11,100 points of cause built up in the 2008-09 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 behaviour suggests the arrival of a bear market.

Figure 5



The last Point of Support, the Count Line and Upside Price Projections to DJIA 17,600–19,200

The pullback or back-up after the sign of strength 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 P&F chart. Along the 8,100 level counting from right to left there were 37 columns of three point reversals for a total P&F 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.

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.

Author's note: The article gained its title: "The Wyckoff Method Applied in 2009: A Case Study of the U.S Stock Market" as it is based upon a presentation by the same name that I gave at the 22nd Annual IFTA Conference in Chicago, Il., U.S.A on October 8, 2009.

Appendix

Wyckoff Point and Figure Projection of the S&P 500 2009 Low

This is the projection of the S&P 500 cash index from the 2007 high to the 2009 low using Wyckoff Point and Figure techniques and shows the points when the market gives clues that it is entering into a trading range and turning down.

The trading range projections points are from the Preliminary Supply (PSY) to the point labeled as the "Ice Hole Failure." The idea here is that the market has fallen through the ice (FTI) and it attempts to get back up above it. Failing to find a hole back through the ice, it drowns and sinks down. Another way to look at this point is the standard "action" of thrusting down and "test", where the test shows resistance to any further climbing.

The points chosen for the projection are the most obvious points when seen from a point and figure chart.

In Figure 8 the settings are for 20 points per box with a 3 box turn around (total of 60 points). The projection range is shown in brown.

This technique projected the S&P 500 to within 10 points of the low off the conservative estimate point.

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The Wyckoff Method Applied in 2009: A Case Study of the U.S Stock Market, Power Point Presentation, Hank Pruden, 22nd Annual IFTA Conference, Chicago, Il., USA, 2009.

Charts and Data

Courtesy:

Publicharts, San Jose, California, USA, 2009.

Institute for Technical Market Analysis, Golden Gate University, San Francisco, CA, USA.

Figure 6
S&P 500 Cash Index

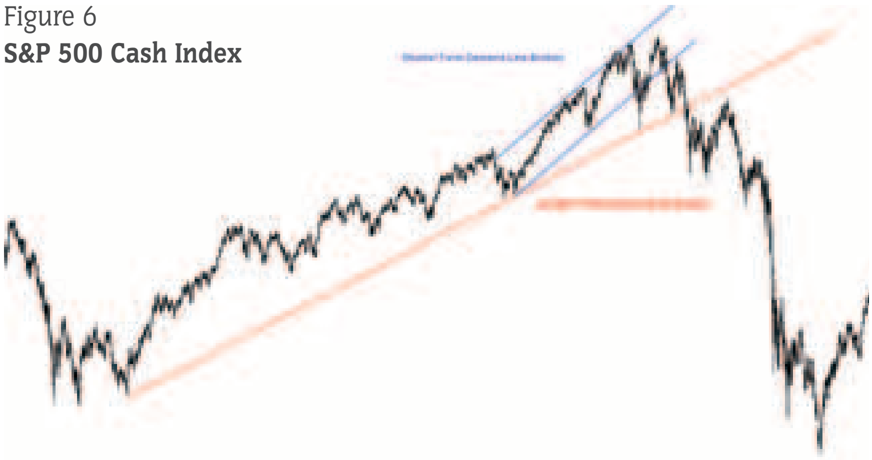
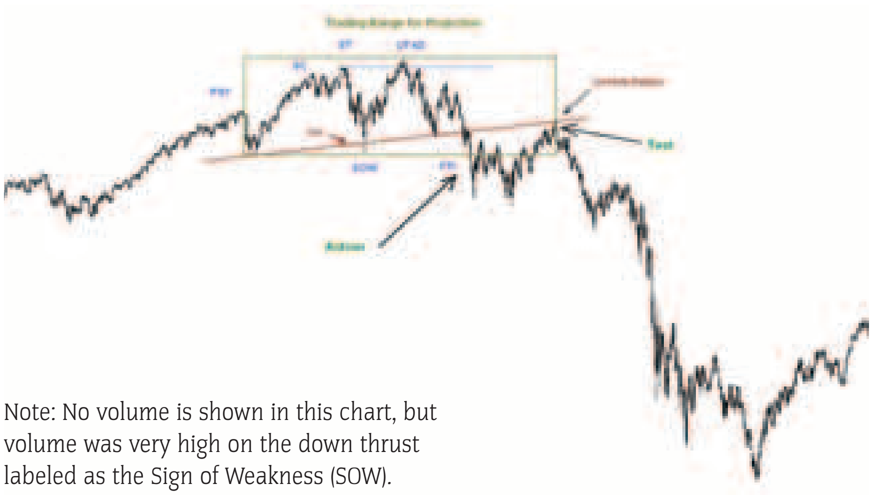
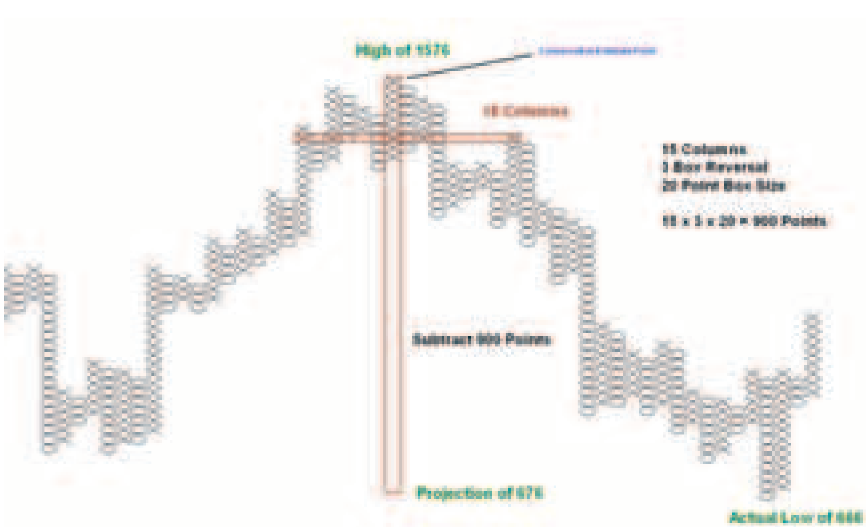


Figure 7
A possible Wyckoff interpretation



Note: No volume is shown in this chart, but volume was very high on the down thrust labeled as the Sign of Weakness (SOW).

Figure 8
Point and Figure chart of the S&P 500



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Implications for Risk Management and Regulation: A study of long-term dependence in the Credit Default Swap (CDS) Indices Market

by Vinodh Madhavan and Hank Pruden

"There is nothing either good or bad, but thinking makes it so"

William Shakespeare, Hamlet, Prince of Denmark

Credit Default Swaps, as the name indicates, are credit instruments used by banks, non- banking financial institutions, hedge funds and investors, to shift risk from one party to another[i].

These instruments are rife with controversy and opposing arguments with regard to pertinent regulatory standards aimed at ensuring requisite checks and balances in the system. The authors of this study do not wish to take sides in such arguments. Rather, the authors wish to shed light upon the nature and degree of market risk inherent in CDS instruments, and hence help regulators to calculate the level of regulatory reserves that ought to be mandated to avert extreme disasters or meltdowns in the future. In other words, the authors wish to ascertain how high a dam of dollar reserves ought to be constructed to avoid the equivalent of a 100 year flood. If the underlying behavioural patterns of the CDS markets mimic a coin toss, then successful change in spread levels are independent of one another. Consequently, the level of regulatory reserves can be much less, as opposed to a scenario wherein the underlying behavioural dynamics of CDS markets are characterised by fat-tailed distribution and long-term dependence. Long memory, or long-term dependence, describes the correlation structure of a series at long lags. If a series exhibits long-term dependence, it reflects persistent temporal dependence even between distant observations[ii]. Presence of high long-term dependence calls for draconian regulation.

The empirical issue being dealt with in this study is akin to questions encountered in hydrology. In hydrology, the key question is "How high a dam should we build?" The celebrated answer to the question in the world of hydrology is associated with an Englishman named Harold Edwin Hurst[iii] who undertook path-breaking studies of the river Nile in the 20th century for the purpose of informing the British Government of how high a dam should they build at Aswan, Egypt to control the floods during extremely wet years and at the same time create reservoirs of water for irrigation during years of drought. Hurst discovered that the true behaviour of the river Nile exhibited a power law, as opposed to a simple coin toss.

Traditional models in hydrology assumed precipitation to be random and Gaussian in nature. Gaussian distribution implies that the precipitation levels follow the normal probability distribution, with successive years' precipitations either mutually independent or with a short memory. Independence implies that a large precipitation level in one year has no aftereffect on the following years, while "short memory" process implies that aftereffects die within a few years. Gaussian models underestimated the durations of the longest drought or the intensity of floods in a short time. Long periods of drought can be extremely long, while the extreme levels of precipitation can be so extreme that they change the average precipitation level of the whole time period within which the extreme precipitation event falls.[iv]

Mandelbrot and his co-authors[v, vi, vii] refined the concepts and techniques created by Hurst, and applied them to financial markets. In doing so, Mandelbrot, his followers, and critics discovered behaviour in financial markets that ranged from near-Gaussian phenomena to extremely one-sided fat-tailed distributions. Mandelbrot's refinement of Hurst's original methodological contribution is referred to as the "Classical R/S method" in the literature. In honour of Hurst, Mandelbrot labeled the long-term dependence coefficient of any time series as H. Employment of the Classical R/S method, also known as Rescaled Range estimation technique, on a Gaussian distribution would yield an H value of 0.50. H value of $0.50 < H < 1$ reflects positive long-term dependence in the time series, while $0 < H < 0.50$ implies anti-persistence phenomenon in the time series. Positive long-term dependence implies that a larger price-point/spread level is likely to be followed by a large price-point/spread level, while anti-persistence behaviour implies that a larger price-point/spread level is bound to be followed by a small price-point/spread level.

The authors' arguments, pertaining to the proper level of regulatory reserves needed to guard against extreme hazards in CDS markets, are based on the following table that lists the different securities and their respective H values based on available empirical data.[viii]

As seen later in this study, the findings revealed H values of 0.56 and 0.58 pertaining to American and European CDS indices datasets

Table 1
Classical R/S Analysis of Individual Stocks

	H value
S&P 500	0.78
IBM	0.72
Xerox	0.73
Apple	0.75
Coca-Cola	0.70
Anheuser-Busch	0.64
McDonald's	0.65
Niagara Mohawk	0.69
Texas State Utilities	0.54
Consolidated Edison	0.68

Source: E E Peters, *Chaos and Order in the Capital markets: A New View of Cycles, Prices, and Market Volatility*, John Wiley & Sons, Inc. New York, 1991, pp.88

respectively. Put differently, despite the non-Gaussian nature of CDS indices, long-term dependence in CDS indices are closer to the relatively sedate behaviour of utility stocks, like Texas State utilities as seen in the above table. Further, the H values pertaining to CDS indices are far below the H levels pertaining to hi-tech stocks such as Apple and IBM.

To arrive at the foregoing conclusion, the authors wish to take the readers through their study of empirical data collected by Dr. Madhavan on American (CDX.NA.IG) and European (iTraxx. Europe) CDS Indices.[ix] These dissertation datasets were then subjected to Classical R/S analysis to ascertain their H values using methodology employed by Mulligan[x].

To sum up, this paper is aimed at analysing the long-term dependence in Investment Grade Credit Default Swap (CDS) indices of US and Europe. For this exercise, the authors have chosen the two most liquid CDS indices, namely CDX.NA.IG of North America and iTraxx. Europe of Europe.

Both CDX.NA.IG and iTraxx.Europe trade in spreads. Buying and selling the indices is similar to buying and selling portfolios of loans or bonds. CDX.NA.IG and iTraxx.Europe each comprise 125 equally-weighted reference entities. Each entity in the index is referenced to an underlying bond/obligation. As a result, the buyer of the CDS index gains exposure to the 125 underlying obligations. Therefore, the buyer of the CDS index, who takes on credit risk of the 125 reference obligations, is the protection seller. On the other hand, the seller of the CDS index who offloads his/her credit risk exposure to underlying reference obligations is the protection buyer. Simply put, by selling the index the protection buyer passes on the exposure to another party and by buying the index, the protection seller takes on credit risk from the counterparty. When an index is rolled out, the Mark-To-Market (MTM) value of the CDS index and the coupon that needs to be paid by the protection buyer to the protection seller on a quarterly basis is one and the same. However, the MTM spread value changes in accordance with the market's evolving assessment of the default risk of the reference entities. The market's fear of a potential default would be reflected by a sudden surge in the MTM spread values of the CDS index. On the other hand, the market's acknowledgement of the healthy state of reference entities would be reflected by a fall in MTM spread values. Price is inversely related to spread. An increase in spreads reduces the price of the CDS index. As a result, upfront payment is exchanged between the counterparties at the initiation and close of the trade in accordance with evolving changes in index spreads (and price).

Both CDX and iTraxx indices roll every six months. In other words, a new series is created every six months. The first series of CDX.NA.IG came into effect on October 21, 2003, while the first series of iTraxx Europe came into effect on June 21, 2004. Although, the old series continues trading, liquidity is concentrated on the most recent series at any point of time. Accordingly, this study takes into account data pertaining to only the most recent CDX.NA.IG series starting from April 3, 2004 to April 6, 2009 and the most recent iTraxx.Europe series between June 21, 2004 and April 6, 2009. Also, both CDX.NA.IG and iTraxx. Europe indices are available in various maturities such as three, five, seven and ten years. For this study, the authors consider daily spread data pertaining to a ten year maturity only. With regard to the pricing mechanism, licensed dealers determine the spread for each index and maturity. This is done through a dealer call in Europe (iTraxx). In North America (CDX), the licensed dealers send Markit, the company which owns and administers these indices, an average spread value. The median of the average spread values received by Markit becomes the fixed spread for the index. The study takes into account the mid-value of the daily closing bids and asks spread levels of iTraxx.Europe and CDX.NA.IG

Taking cognizance of the non-normality of the underlying datasets pertaining to North America and Europe, the authors employ Classical R/S analysis[xi, xii, xiii] to not only understand the underlying dynamics of the two indices, but also to draw-upon pertinent regulatory implications. Section 1 will provide a brief overview of relevant literature. Section 2 details the methodology. The authors present the findings pertaining to Classical R/S method in section 3. In section 4, the authors draw regulatory implications based on the study's findings. Annexure 1 offers a snapshot of the mathematical underpinnings behind the Classical R/S analysis. Annexure 2 offers information pertaining to datasets utilised and the operations employed. Annexure 3 constitutes the mathematical underpinnings behind the Modified Rescaled Range estimation technique[xiv]. And, annexure 4 contains the test outcomes obtained when both the American and European datasets were subjected to Lo's modified Rescaled Range estimation technique.

Section 1: Relevant Literature

Periods of acute and unprecedented turbulence in markets enhance researchers' threshold for seeking alternative explanations – explanations that run contrary to inferences based on well-established Gaussian models. Such excursions into uncharted territories reflect not only the evolving realisation of the complexity of the financial markets, but are also an acknowledgement of the limitations of Gaussian models – models whose underlying mathematical and statistical assumptions fail to truly reflect real-world characteristics of asset prices. Such non-conventional research efforts paved the way to studies that tested for less-frequent long-term dependence as opposed to highly-frequent short-term dependence amidst asset prices. A time series characterised by long-term dependence coupled with non-periodic cycles is termed fractal.[xv]

Prior studies have explored long-term dependence characteristics amidst a variety of assets including and not limited to (1) stock prices[xvi, xvii, xviii] (2) stock, bond and relative stock bond returns[xix, xx] (3) foreign stock returns[xxi] (4) exchange rates[xxii, xxiii, xxiv] (5) commodity and stock index futures[xxv, xxvi] (6) gold prices[xxvii] and (7) Euro-dollar & T-bill futures[xxviii].

Despite the foregoing studies, not much is known about the presence of long-term dependence (if any) in CDS indices. These credit default swap instruments have been increasingly in the news since August 2007 because of their role in the recent credit crisis that originated in the United States, which then paved way for a synchronised global recession. It is notable that immense CDS exposures of certain market players nearly pushed the financial markets towards systemic collapse. In addition, at a broader level, a lot of unpleasant events have taken place in the credit markets that include but not limited to insolvency of a prime-broker, a run on money-market funds, immense injection of liquidity, concurrent interest rate cuts, and an unprecedented amount of government subsidies for financial and non financial firms owing to economic and political reasons.

Domestic and international regulatory efforts aimed at creating appropriate oversight that would prevent the recurrence of recent disasters, are currently in the making. It is the authors' belief that a major component of an effective overarching regulatory framework would be an appropriate globally-synchronised regulatory mechanism that helps regulators capture and consequently act upon financial market participants' evolving appetite for CDS and CDS-based products. It is therefore desirable to shed light upon the long-term dependence and potential risks inherent in the CDS indices market. This calls for regulators to gain adequate understanding of the underlying dynamics of the CDS markets. And it would be much easier to gain this requisite understanding on a section of CDS markets that is most liquid and transparent, namely Investment Grade (IG) Credit Indices of US (CDX.NA.IG) and Europe (iTraxx.Europe). And this study, aimed at understanding the underlying long-term dependence (if any) in the CDS indices market, is a step in this direction.

Section 2: Methodology

To learn more about the American and European datasets considered for this study, please refer to Annexure 2.

The Classical Rescaled Range estimation technique was employed on iTraxxC and CDXC values to test for long-term dependence. Annexure 1 offers the mathematical underpinnings behind Hurst's formula and Mandelbrot's Classical R/S method. As part of Mandelbrot's Rescaled Range estimation technique, the original iTraxxC and CDXC samples need to be partitioned into different sub-samples of varying lengths k. In this regard, the authors adhered to the methodology followed by Mulligan in his paper on fractal analysis of foreign exchange markets[xxix]. The authors considered a minimum sub-sample size of five days for this study. The authors then partitioned the original dataset into many sub-samples of varying sizes ranging from a minimum of $k = 5$ to a maximum value of k that would allow the original dataset to be partitioned into at least two equal sub-samples ($k = N/2 = 625$).

To better illustrate this methodology, let's consider $k = 6$. In this case, the authors partitioned the dataset into 208 sub-samples ($1250/6 \sim 208$); each sub-sample constitutes sequential data pertaining to the percentage change in daily spreads (iTraxxC, CDX) for six consecutive days. Then for each sub-sample, the range R and the standard deviation S was calculated. Then R/S values for each of the 208 sub-samples were calculated. Finally an average R/S for all 208 equally-sized, equally-spaced sub-samples was calculated. The outcome was labeled as R/S measure for $k = 6$. This methodology was followed for each value of k ranging from $k = 5$ to $k = 625$. Then the different R/S values were plotted against their respective k values in the logarithmic space.

Section 3: Findings

The descriptive statistics pertaining to iTraxxC and CDXC are shown in Tables 2.1, 2.2 and 2.3.

No imputation methodology was employed by the authors to fill-in the missing values. Put simply, missing values were treated as missing. It is notable that the findings pertaining to the Kurtosis, Skewness, Kolmogorov-Smirnov and Shapiro-Wilk tests reflect the presence of non-normality in both the iTraxxC and CDXC datasets.

Having viewed the descriptive statistics pertaining to both the datasets, the authors then subjected the datasets to the Classical Rescaled Range estimation technique. This resulted in the estimation of R/S values for varying sub-sample sizes (k) ranging from 5 to 625. The following are the log R/S values versus the log k scatter-plots pertaining to both iTraxxC and CDXC datasets.

Table 2.1
Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
iTraxxC	1166	93.3%	**84**	**6.7%**	1250	100.0%
CDXC	1027	82.2%	**223**	**17.8%**	1250	100.0%

Table 2.2: **Descriptive Statistics: iTraxxC & CDXC**

		iTraxxC		CDXC	
		Statistic	Std. Error	Statistic	Std. Error
Mean		0.0013	0.0009	0.0009	0.0008
95% Confidence Interval for Mean	Lower Bound	-0.0004		-0.0007	
	Upper Bound	0.0031		0.0025	
5% Trimmed Mean		0.0008		0.0006	
Median		-0.0006		0.0000	
Variance		0.0009		0.0007	
Std. Deviation		0.0305		0.0263	
Minimum		-0.1802		-0.2102	
Maximum		0.1919		0.1984	
Range		0.3722		0.4085	
Interquartile Range		0.0209		0.0159	
Skewness		**0.6487**	0.0716	**0.2172**	0.0763
Kurtosis		**7.1959**	0.1432	**13.0316**	0.1525

Table 2.3: **Tests of Normality: iTraxxC & CDXC**

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	Df	Sig.
iTraxxC	.137	1166	**.000**	.878	1166	**.000**
CDXC	.144	1027	**.000**	.810	1027	**.000**

a. Lilliefors Significance Correction

Figure 5
iTraxxC: log(n) vs log(R/S) Scatter Plot

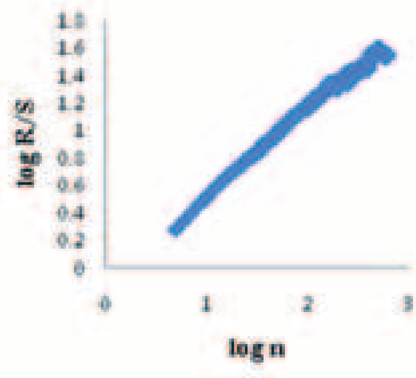
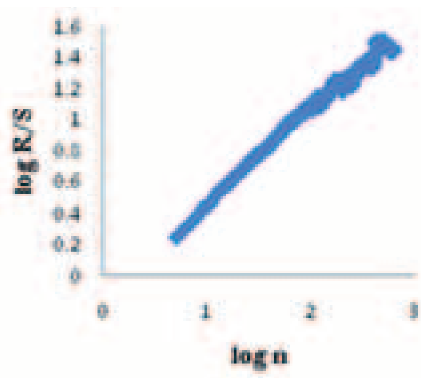


Figure 6
CDXC: log(n) vs log(R/S) Scatter Plot



The following outcomes pertaining to iTraxxC and CDXC were gained by regressing the different log R/S values against log k values to estimate the Hurst-Coefficient H.

iTraxxC Regression Procedure

Table 3.1: **Regression Statistics**

Multiple R	0.9903
R Square	0.9807
Adjusted R Square	**0.9807**
Standard Error	0.0320
Observations	621.0000

Table 3.2: **ANOVA**

	df	SS	MS	F	Significance F
Regression	1.0000	32.1278	32.1278	**31456.0213**	**0.0000**
Residual	619.0000	0.6322	0.0010		
Total	620.0000	32.7600			

Table 3.3: **Regression coefficents**

	Co-efficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.0058	0.0078	-0.7418	0.4585	-0.0212	0.0096	-0.0212	0.0096
logn	**0.58**	0.0033	177.3585	0.0000	0.5712	0.5840	0.5712	0.5840

CDXC Regression Procedure

Table 4.1: **Regression Statistics**

Multiple R	0.9885
R Square	0.9771
Adjusted R Square	**0.9771**
Standard Error	0.0336
Observations	621.0000

Table 4.2: **ANOVA**

	df	SS	MS	F	Significance F
Regression	1.0000	29.8613	29.8613	**26441.2664**	**0.0000**
Residual	619.0000	0.6991	0.0011		
Total	620.0000	30.5604			

Table 4.3: **Regression coefficents**

	Co-efficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.0453	0.0083	-5.4909	0.0000	-0.0615	-0.0291	-0.0615	0.0291
logn	**0.56**	0.0034	162.6077	0.0000	0.5501	0.5636	0.5501	0.5636

As evidenced in tables 3.3 and 4.3, the slope of the regression lines reflect prevalence of positive long-term dependence in both iTraxxC (H: 0.58) and CDXC (H: 0.56) datasets.

In the following section, the authors draw implications pertaining to regulation and risk management, based on H values obtained by employing the Classical Rescaled Range estimation technique.

Section 4: Regulatory Implications for this study

As evidenced in section 3, the H values for iTraxxC and CDXC are 0.58 and 0.56 respectively. It is notable that both iTraxxC and CDXC are non-normal in nature. Despite their non-normality, their long-term dependence co-efficient is more in line with less-risky traditional companies.

As seen in Table 5, the H values of iTraxxC and CDXC at 0.58 and 0.56 are far below H values pertaining to high-tech stocks like Apple and IBM; and the extent of long-term dependence in iTraxxC and CDXC is similar to what was witnessed in Texas State Utilities.

Consequently, the authors believe that regulators should realise that not all CDS markets are toxic in nature. This is not an attempt by the authors to profess need for no regulation. Having witnessed the near collapse of financial systems in 2007-2008, the authors understand and duly appreciate the need for financial regulation pertaining to CDS instruments, as part of the broader financial overhaul. Having said so, it is of utmost importance that regulators exercise moderation and prudence, when it comes to formulating regulations pertaining to different CDS instruments. For instance, since not all CDS instruments are equally toxic, it would be wrong to paint all CDS instruments with the same brush. In fact, Investment-grade CDS indices such as and limited to CDX.NA.IG and iTraxx. Europe appear to be less-riskier in comparison to high-tech stocks. Hence it would be imprudent to treat these CDS indices on equal terms to synthetic Collateralized Debt Obligations (CDOs) which have created a considerable amount of havoc in the market place.

Table 5
Classical R/S Analysis of Individual Stocks

	H value
S&P 500	0.78
IBM	0.72
Xerox	0.73
Apple	0.75
Coca-Cola	0.70
Anheuser-Busch	0.64
McDonald's	0.65
Niagara Mohawk	0.69
Texas State Utilities	0.54
Consolidated Edison	0.68

Source: E E Peters, *Chaos and Order in the Capital markets: A New View of Cycles, Prices, and Market Volatility*, John Wiley & Sons, Inc. New York, 1991, pp.88

The study's findings reflects the need for regulators to acknowledge prevalence of certain benign CDS markets within the overall CDS landscape that is currently labeled as highly toxic for a variety of reasons. Regulatory discussions and consequent actions that disregard this revelation, would translate into a one-size-fits-all approach that caters more towards contemporary populist angst against broader CDS markets, as opposed to rightly-targeted regulatory actions that acknowledge and appropriately account for different risk patterns behind different CDS markets.

Future research aimed at identifying the nature of risk patterns amidst different segments of the broader CDS market is the need-of-the-hour. Also, according to Lo[xxx] Classical R/S method does not accommodate for short-range dependence. Consequently, long-term dependence may not be truly long-term in nature. It may be a statistical manifestation of inherent short-term dependence in the time series. The authors subjected both iTraxxC and CDXC to Lo's Modified Rescaled Range estimation technique[xxxi] which appropriately accounts for short-term dependence, non-normal innovations, and conditional heteroscedasticity. Annexure 3 offers the mathematical underpinnings behind Lo's Modified Rescaled Range estimation technique, while annexure 4 constitutes the test outcomes obtained by the authors when they subjected iTraxxC and CDXC to Lo's method. The results pertaining to the Modified Rescaled Range estimation technique reveal prevalence of short-term dependence. This revelation offers huge potential for future research in CDS markets, from a technical analysts' perspective.

Annexure 1: Hurst's Formula and Classical R/S Method

Hurst's pioneering contribution in Hydrology was centered on determining the reservoir storage required for a given stream, to guarantee a given draft. According to Hurst, if a long-term record of annual discharges from the stream is available, then the storage required to yield average flow each year is obtained by computing the cumulative sums of the departures of annual totals from the mean annual total discharge. The range from the maximum to the minimum of such cumulative totals is taken as the required storage R.

Consequently R indicates how big the reservoir ought to be to avoid floods or drought. R could be calculated by employing factors such as and limited to a) σ which reflects the standard deviation of annual discharges from one year to the next, b) N which indicates the number of years involved in the study, and c) the power-law exponent that drives the whole equation.

Hurst's formula is given as follows.

$$\log\left(\frac{R}{\sigma}\right) = K \log\left(\frac{N}{2}\right)$$

Removing the logs, the equations is shown as follows

$$R = \sigma\left(\frac{N}{2}\right)^{K}$$

Mandelbrot refined the above Hurst formula and in the process introduced a Hurst exponent labeled as H[xxxii]. Mandelbrot's Rescaled Range statistic is widely used to test long-term dependence in a time series. Contrary to conventional statistical tests, Mandelbrot's Classical R/S method does not make any assumptions with regard to the organisation of the original data. The R/S formula simply measures whether, over varying periods of time, the amount by which the data vary from maximum to minimum is greater or smaller than what a researcher would expect if each data point were independent of the prior one. If the outcome is different, this implies that the sequence of data is critical.

Mandelbrot's classical R/S method requires division of the time series into a number of sub series of varying length k. Then, log[R(k)/S(k)] values are plotted against log k values. Following such a scatter plot, a least squares regression is employed so as to fit an optimum line through different log R/S vs. log k scatter plots. The slope of the regression line yields H.

To better illustrate Mandelbrot's approach to R/S estimation, let us assume a return r denoting a profit or loss based on an asset price movement over different time periods such as a day, two days, three days, and so on up to the length of the full-time series (denoted as n). Then the average return (denoted by $\bar{r}_n$ for the entire time-period n is calculated. Then, for each shorter time period (k), the difference between the return in that time period and the average return pertaining to the whole time series is calculated. A running total of all such differences reflect the cumulative deviation of shorter time-period returns vis-à-vis the average return of the total time series. Then the maximum and minimum of such accumulated deviations is found out. Subtraction of one from the other offers the range from peak to trough in accumulated deviations. This constitutes the numerator of the R/S estimation formula. The denominator is a conventional measure of the standard deviation of the time series. The R/S estimation equation is shown below.

$$\frac{R}{S} = \frac{Max_{1\le k\le n}\sum_{j=1}^{k}(r_j - \bar{r}_n) - Min_{1\le k\le n}\sum_{j=1}^{k}(r_j - \bar{r}_n)}{[\frac{1}{n}\sum_j (r_j - \bar{r}_n)^2]^{1/2}}$$

For $1 \le k \le n$.

Annexure 2: Data

Figure A2.1
iTraxx spreads – Area Plot

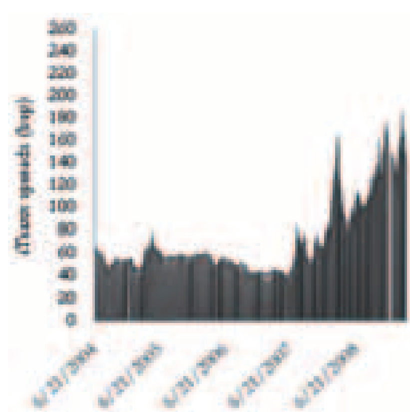
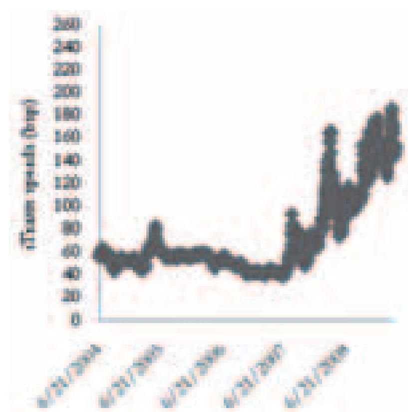


Figure A2.2
iTraxx spreads – Line Plot



Both the CDX and iTraxx datasets contain 1250 observations pertaining to the mid-value of daily closing bid and ask spreads between June 21, 2004 and April 3, 2009. Figures A2.1 to A2.4 are the line and area plots pertaining to daily closing mid values of iTraxx.Europe and CDX.NA.IG.

It has to be noted that prior studies on long term dependence[xxxiii]

Figure A2.1
iTraxx spreads – Area Plot

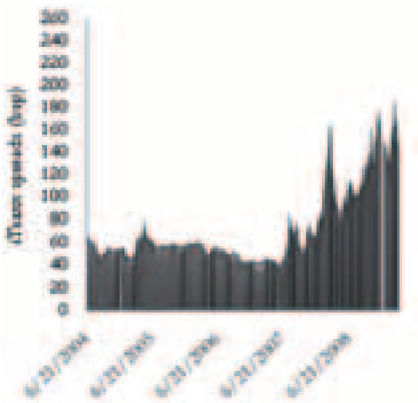
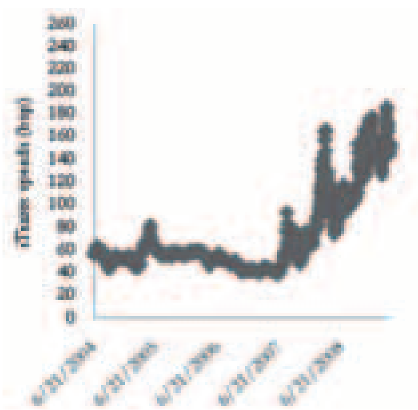


Figure A2.2
iTraxx spreads – Line Plot



operationalise asset returns as

$$X_t = ln\left(\frac{P_t}{P_{t-1}}\right)$$

where X_t is the logarithmic return of an asset at time t, and P_t of an asset at time t, while P_{t-1} is the price of the asset at time t-1. Then classical rescaled range estimation technique is employed on sequential logarithmic returns to test for long-term dependence.

Unlike traditional assets, it is notable that this study deals with closing spreads expressed in basis points (100 bsp = 1%). Accordingly, the authors aim to test for long-term dependence with regard to percentage change in daily closing spreads, which in-turn is operationalized as follows

$$X_t = \left(\frac{s_t - s_{t-1}}{s_{t-1}}\right)$$

Where s_t is the mid-value of the closing bid and ask spreads at time t; s_{t-1} is the mid value of the closing bid and ask spreads at time t-1, and X_t is the percentage change in spreads from time t-1 to t. When expressed in terms of the indices being considered for this study, the above relationship translates as follows

$$iTraxxC_t = \left(\frac{iTraxx_t - iTraxx_{t-1}}{iTraxx_{t-1}}\right)$$

$$CDXC_t = \left(\frac{CDX_t - CDX_{t-1}}{CDX_{t-1}}\right)$$

Where $iTraxx_t$ is the mid-value of the closing bid and ask spreads of iTraxx at time t; $iTraxx_{t-1}$ is the mid value of the closing bid and ask spreads of iTraxx at time t-1; $iTraxxC_t$ is the percentage change in iTraxx mid-value spreads at time t with respect to time t-1; CDX_t is the mid value of the closing bid and ask spreads of CDX at time t; CDX_{t-1} is the mid value of closing bid and ask spreads of CDX at time t-1; and $CDXC_t$ is the percentage change in CDX mid-value spreads at time t with respect to time t-1. Figures A2.5 and A2.6 are area plots pertaining to iTraxxC and CDXC respectively.

Figure A2.5
iTraxxC: Area Plot

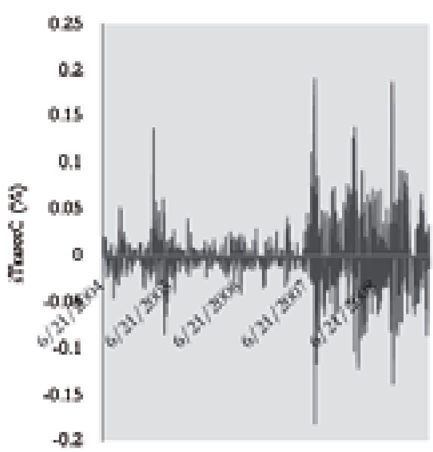
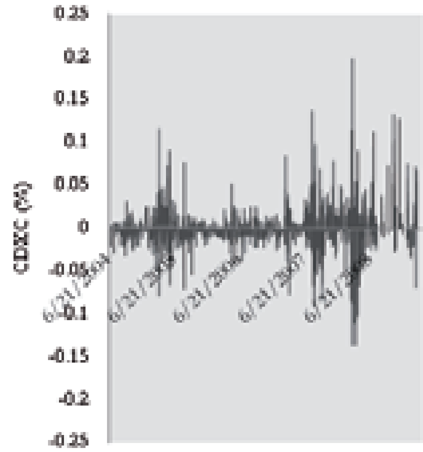


Figure A2.6
CDXC: Area Plot



Annexure 3: Modified Rescaled Range Estimation Technique

According to Lo[xxxiv], Mandelbrot's Rescaled Range estimation technique and its subsequent refinements were not designed to distinguish between short-range and long-range dependence. Consequently, any empirical investigation of long-term dependence in asset prices must first account for the presence of higher frequency autocorrelation. Also, the distribution of its test-statistic is not well-defined in the case of the Classical R/S method. Further, Classical R/S estimates are vulnerable to potential heterogeneity in underlying data. Consequently, tests for long-term dependence should account for conditional heteroscedasticity. To deal with these concerns, Lo proposed a modified R/S technique.

Lo's modified R/S estimation procedure accommodates short-term dependence, non-normal innovations, and conditional heteroscedasticity, wherein the test examines the null hypothesis of the short-term dependence process against presence of long- term dependence. Modified R/S statistic denoted as Q_T is calculated as follows

$$Q_T = R / S_T \ (q)$$

Where

$$R = Max_{1 \le i \le T} \sum_{t=1}^{i}(x_t - x*) - Min_{1 \le i \le T} \sum_{j=1}^{i}(x_t - x*)$$

And S_T^2 is heteroscedasticity and autocorrelation-consistent variance estimator.

$$s_T(q) = \left\{ \sum_{i=1}^{T} \frac{(x_i - x*)^2}{T} + 2\sum_{j=1}^{q} \tau_j(q) \left(\frac{\sum_{i=j+1}^{T}(x_i - x*)(x_{i-j} - x*)}{T} \right) \right\}^{1/2}$$

Where the weighing function $\tau j\,(q) = 1 - |j/\xi T|$, and
x* is the mean of the time series.
The truncated lag q is calculated in accordance with Andrew's study[xxxv] as shown below

$$q = Int[\xi_T], \xi_T = \left(\frac{3T}{2}\right)^{1/3} \left(\frac{2\delta}{1-\delta^2}\right)^{2/3}$$

Where δ is the first-order autocorrelation coefficient.

The denominator of the modified R/S estimator normalises the range measure by sample variance and weighted sum of sample autocovariances for q>0. The modified R/S test is based on R/S values computed for the entire time series, while the Classical R/S test estimates the Hurst coefficient by regressing R/S values of different sub series on their corresponding length.

Contrary to findings pertaining to prior studies that employed Classical R/S estimation procedure, Lo[xxxvi] demonstrates that there is little evidence of long term dependence in US stock returns, once short-term dependence and conditional-heteroscedasticity are accounted for in the calculations.

Annexure 4: Test outcomes pertaining to Modified Rescaled Range Estimation Technique

Unlike Mandelbrot's Rescaled Range estimation technique, Lo's Modified Range estimation technique warrants analysis of the entire dataset as opposed to sub-samples of varying sizes. Since Lo's technique accommodates for auto-covariance while calculating the standard deviation of the underlying dataset, the authors estimated the first-order auto-correlation coefficient (δ) of both iTraxxC and CDXC datasets. The authors then utilised the first-order autocorrelation coefficients to calculate the truncated lag q for both iTraxxC and CDXC. The authors then utilised the q values obtained to calculate heteroscedasticity and the autocorrelation-consistent standard deviation of the dataset. It has to be noted that the numerator (range) in both Classical Rescaled Range estimation and Modified Rescaled Range estimation techniques remain the same. Finally, the authors calculated Lo's critical value as shown below:

$$V = \frac{\left(\frac{R}{S_T}\right)}{n^{\left(\frac{1}{2}\right)}}$$

To test whether the long-term dependence as evidenced above is truly long-term in nature, or a statistical manifestation of underlying short-term dependence in the datasets, the authors subjected the entire iTraxxC and CDXC datasets to Lo's Modified Rescaled Range estimation technique.

Before providing the findings pertaining to Lo's technique, it would be appropriate to provide the first-order auto-correlation coefficients and truncated q values obtained for iTraxxC and CDXC datasets.

Table A4.1
First-order autocorrelation coefficient & Truncated lags

	δ	q
iTraxxC	.1901	12
CDXC	.0675	11

The following are the critical values that were obtained following Lo's analysis:

Table A4.2
Modified rescaled range technique: Critical Values

	q	V
iTraxxC	12	1.2686
CDXC	11	1.1303

The null-hypothesis in the case of Lo's analysis is the absence of long-term dependence in time series. Further, the critical values (V) at 10% and 5% significance levels, as tabulated by Lo[xxxvii], are 1.620 and 1.747 respectively. A higher value of V that exceeds critical values would offer sufficient grounds to reject the null hypothesis. As seen above, V statistics pertaining to both iTraxxC and CDXC fall well below the critical values. This reflects that the long-term dependence amidst iTraxxC and CDXC datasets as indicated by Rescaled Range estimation technique is actually a statistical manifestation of short-term dependence. Further, the long-term dependence vanishes once the estimation technique makes appropriate adjustments for short-term dependence and conditional heteroscedasticity. IFTA

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Moving Mini-Max – A New Indicator for Technical Analysis

by Zurab Silagadze

Abstract

A new indicator for technical analysis is proposed which emphasises maximums and minimums in price series with inherent smoothing and has the potential to be useful in both mechanical trading rules and chart pattern analysis.

Introduction

Despite the widespread use of technical analysis in short-term marketing strategies, its usefulness is often questioned. According to the efficient market hypothesis[i], no one can ever outperform the market and earn excess returns by only using the information that the market already knows. Therefore, technical analysis, which is based on price history, is expected to be of the same value for efficient markets as astrology: "Technical strategies are usually amusing, often comforting, but of no real value"[ii].

However, the efficient market hypothesis assumes that all market participants are rational, while it is a well known fact that human behaviour is seldom completely rational. Therefore, the idea that one can try "to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism on one hand and confidence, excessive optimism, and greed on the other"[iii] does not seem to be completely hopeless.

At least, "by the start of the twenty-first century, the intellectual dominance of the efficient market hypothesis had become far less universal. Many financial economists and statisticians began to believe that stock prices are at least partially predictable"[iv].

Besides, the market efficiency can be significantly distorted at periods of central bank interventions allowing traders to profit by using even very simple technical trading rules.[v, vi]

In any case, it appears that the use of technical analysis is widespread among practitioners, becoming in fact one of the invisible forces shaping the market. For example, many successful financial forecasting methods seem to be self-destructive[vii, viii] their initial efficiency disappears once these methods become popular and shift the market to a new equilibrium.

Technical analysis is based on the supposition that asset prices move in trends and that "trends in motion tend to remain in motion unless acted upon by another force" (the analogue of Newton's first law of motion)[ix]. The financial forces that compel the trend to change are the subject of fundamental analysis[x]. Efficient markets react quickly to various volatile fundamental factors and to the spread of the corresponding information, leaving little chance to practitioners of either technical or fundamental analysis to beat the market.

However, real markets react with some delay (inertia) to changing financial conditions[xi] and trends in these transition periods can reveal some characteristic behaviour determined by human psychology and corresponding irrational expectations of traders. A skilled analyst can detect these characteristic features with tools of technical analysis alone (although some fundamental analysis, of course, might be also helpful and reduce risks).

Practitioners of technical analysis often use charting (graphing the history of prices over different time frames) to identify trends and forecast their future behaviour[xii, xiii] with peaks and troughs in the price series playing important roles. The location of such local maximums and minimums is hampered by short-term noise in the price series and usually some smoothing procedures are first applied to remove or reduce this noise.

Below an algorithm for searching for local maximums and minimums is presented. The algorithm is borrowed from nuclear physics and it enjoys an inherent smoothing property. A new indicator for technical analysis, the moving mini-max, can be based on this algorithm.

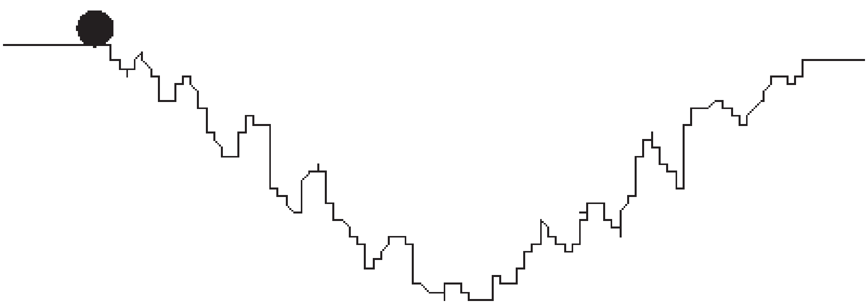
The idea behind the indicator

The idea behind the proposed algorithm can be traced back to George Gamow's theory of alpha decay[xiv]. The alpha particle is trapped in a potential well by the nucleus and classically has no chance to escape. However, according to quantum mechanics it has non-zero, albeit tiny, probability of tunneling through the barrier and thus to escape the nucleus.

Now imagine a small ball placed on the edge of the irregular potential well (see Figure 1). A classical ball will not roll down but will stop in front of the foremost obstacle. However, if the ball is quantum, so that it can penetrate through narrow potential barriers, it will find its way towards the potential well bottom and oscillate there.

Instead of considering a real quantum-mechanical problem, one can only mimic the quantum behaviour to reduce the computational complexities. In previous studies[xv], suitably defined Markov chains were used for this goal. The algorithm that emerged proved to be useful and statistically robust in γ-ray spectroscopy[xvi, xvii]. Two-dimensional generalizations of the algorithm have been researched recently, notably by Morhac[xviii, xix].

Figure 1
A schematic illustration of the idea behind the algorithm: a small quantum ball can penetrate through narrow barriers and find its way downhill despite the noise in the potential well shape.



The indicator

Let S_i, $i=1,\ldots,n$ be a price series in a time window. For our purposes, the moving mini-max of this price series, $u(S)_i$, can be considered as a non-linear transformation

(1)
$$u(S)_i = \frac{u_i}{u_1 + u_2 + \ldots + u_n},$$

where $u_1=1$ and u_i, $i>1$ are defined through the recurrent relations

(2)
$$u_i = \frac{P_{i-1,i}}{P_{i,i-1}} u_{i-1}, \quad i = 2,3,\ldots,n.$$

Evidently, the moving mini-max series satisfies the normalisation condition

(3)
$$\sum_{i=1}^{n} u(S)_i = 1.$$

The transition probabilities P_{ij}, which mimic the tunneling probabilities of a small quantum ball through narrow barriers of the price series, are determined as follows

(4)
$$P_{i,i+1} = \frac{Q_{i,i+1}}{Q_{i,i+1} + Q_{i,i-1}}, \qquad P_{i,i-1} = \frac{Q_{i,i-1}}{Q_{i,i+1} + Q_{i,i-1}}$$

with

(5)
$$Q_{i,i+1} = \sum_{k=1}^{m} \exp\left[\frac{2(S_{i+k} - S_i)}{S_{i+k} + S_i}\right], \qquad Q_{i,i-1} = \sum_{k=1}^{m} \exp\left[\frac{2(S_{i-k} - S_i)}{S_{i-k} + S_i}\right]$$

Here m is the width of the smoothing window. This parameter mimics the (inverse) mass of the quantum ball and therefore governs its penetrating ability. Besides, it is assumed that $S_{i+k} = S_n$, if $i+k>n$, and $S_{i-k}=S_1$, if $i-k<1$.

The moving mini-max $u(S)_i$ emphasises local maximums of the primordial price series S_1. Alternatively, we can construct the moving mini-max $d(S)_i$ which will emphasise local minimums. What is requied is to change $Q_{i,i\pm1}$ in the above formulas with $Q'_{i,i\pm1}$ defined as follows

(6)
$$Q'_{i,i+1} = \sum_{k=1}^{m} \exp\left[-\frac{2(S_{i+k} - S_i)}{S_{i+k} + S_i}\right] \qquad Q'_{i,i-1} = \sum_{k=1}^{m} \exp\left[-\frac{2(S_{i-k} - S_i)}{S_{i-k} + S_i}\right]$$

That is, the sign is changed to the opposite in all exponents while calculating the transition probabilities.

Figure 2 shows $u(S)_i$ and $d(S)_i$ moving mini-maxes in action and highlights their inherent smoothing property.

Possible applications

Possible applications of the moving mini-max are limited only by the imagination of the trader with the most obvious presented here.

Resistance and support lines play an important role in technical analysis. To identify lines of resistance and support, the use of moving averages appears popular among traders. If the price goes through the local maximum and crosses a moving average, we have a resistance line indicating the price from which a majority of traders expect that prices will move lower. A support line materialises when the price crosses a moving average after the local minimum. The support line indicates the price from which a majority of traders feel that prices will move higher. A problem with this is can be that price fluctuations hamper the identification of both the local extremes and the corresponding crossing points with the moving average. In these situations the new indicator can be useful as it automatically suppresses the noise. Using $u(S)$ moving mini-max for both the price and its moving average it allows the search for the crossing points of the corresponding moving mini-maxes to identify resistance lines. Analogously, $d(S)$ moving mini-maxes can be used to search for the support lines.

It is widely believed that certain chart patterns can signal either a continuation or reversal in a price trend. Maybe the most notorious pattern of this kind is the head-and-shoulders pattern[xx, xxi]. For the identification of this pattern, the extreme of the price series needs to be located and the moving mini-max can find an application here.

As an illustration, Figure 3 shows an alleged head-and-shoulders pattern and the corresponding behaviour of the moving mini-max indicators. Note that $u(S)$ and $d(S)$ indicators form a characteristic spindle like pattern at the location of the head-and-shoulders.

As further examples, Figure 4 shows the behaviour of the $u(S)$ and $d(S)$ indicators for a price series with a clear downward trend. While Figure 5 illustrates what happens under the trend reversal.

Conclusion

The examples displayed in this report are just a few of the potential applications of this indicator. Borrowing from nuclear physics, the moving mini-max uses an algorithm with an inherent smoothing quality which has the ability of diffusing some of the noise in the identification of patterns and trends within the landscape of markets. “The classical technical analysis methods of financial indices, stocks, futures, … are very puzzling”[xxii]. It‘s unlikely the new indicator can completely disentangle the puzzlement, but it is hoped that it can add some new flavour and delight to the field of technical analysis.

Acknowledgments

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Figure 2

A price series S_i (top) and its mini-max (bottom) for the smoothing window widths m=3 (left) and m=10 (right). The red line corresponds to the up mini-max $u(S)_i$, which emphasises local maximums, and the blue line – to the down mini-max $d(S)_i$ which emphasises local minimums.

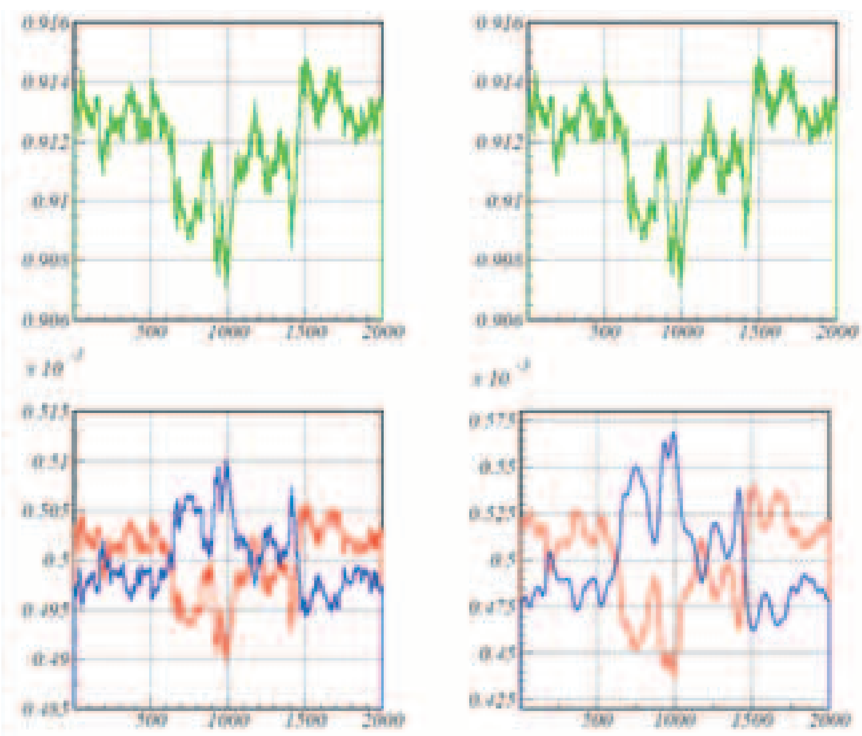

Figure 3

A price series S_i (top) which exhibits a head-and-shoulders pattern and its mini-max (bottom) for the smoothing window width m=5. The red line corresponds to the up mini-max $u(S)_i$ and the blue line – to the down mini-max $d(S)_i$.

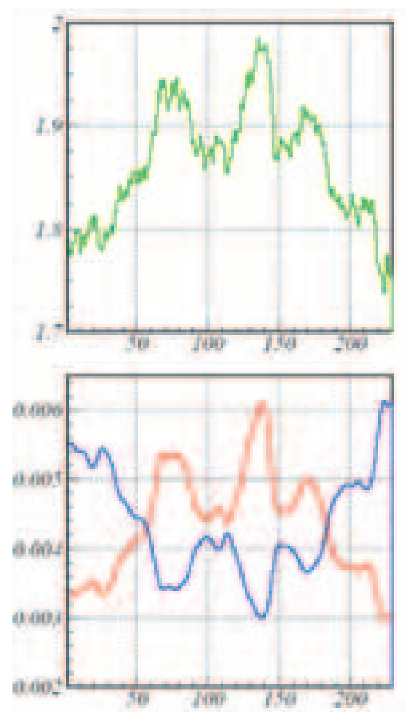

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Figure 4

A price series S_i (top) with a downward trend and its mini-max (bottom) for the smoothing window widths m=3 (left) and m=20 (right). The red line corresponds to the up mini-max $u(S)_i$ and the blue line – to the down mini-max $d(S)_i$.

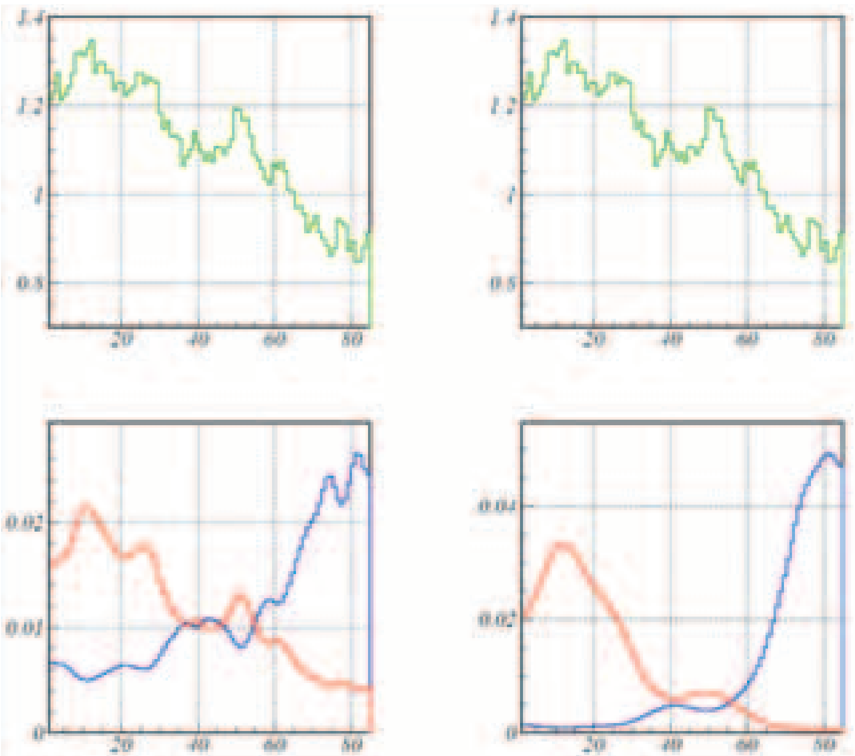
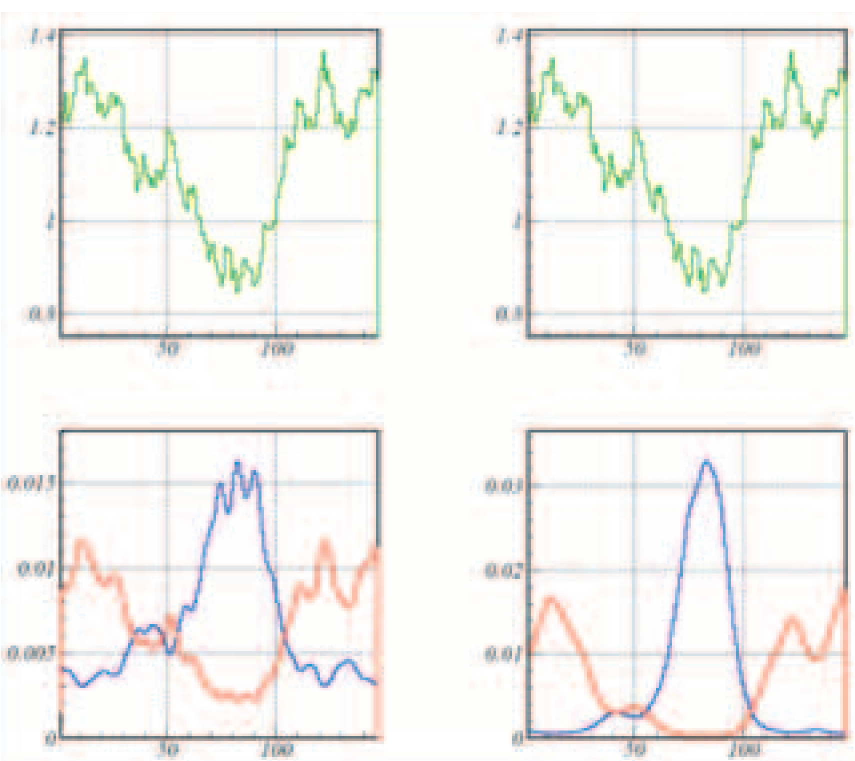


Figure 5

A price series S_i (top) with a trend reversal and its mini-max (bottom) for the smoothing window widths m=3 (left) and m=20 (right). The red line corresponds to the up mini-max $u(S)_i$ and the blue line – to the down mini-max $d(S)_i$.



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Market Dynamics: Modeling Security Price Movements and Support Levels[i]

by Josh Dayanim

Abstract

Market Dynamics presents a method for measuring and forecasting target price, support level, and price movement indicators of traded securities. The method receives historical and optionally projected data such as price, trade volume, earnings, and number of outstanding shares. It then develops a security pricing model that takes into account the received data and generates target price and price movement indicators including expected price change, investment rate, money flow, support ratio, and event time horizon. The security pricing model applies a time derivative approach to the price equation and relies on a conservation of capital principal in its formulation.

Market Dynamics has the wherewithal to be applied to a number of fields including investment management through measurement of security price appreciation potential, as well as technical analysis in determining support or resistance price levels and understanding the underlying mechanism behind these levels and the security price movements.

Introduction

The price of a security may vary pursuant to a number of events, including: an earnings surprise, change in growth rate, change in attractiveness of an industry or asset class, shift in market liquidity and availability of buyers and sellers, change in macroeconomic factors such as inflation and interest rate, or other significant security or market development. Existing security pricing models typically use fundamental analysis or technical analysis in setting a target price or anticipating a price movement.

Fundamental analysts often measure price by using a discounted cash flow model of future expected earnings. This approach relies on research into basic financial information to forecast profits, supply and demand, industry strength, management ability, and other intrinsic matters affecting a security's market value and growth potential[ii]. Thus, price evaluation is based on business performance and assumes that a forecast target price eventually will be reached. However, fundamental analysis often results in differing projections based on growth rate and annuity model assumptions, and suffers from subjective weighting and application of multiple factors affecting price.

Technical analysis relies on chart pattern recognition and the theory that historically these patterns repeat themselves, giving a guide to the likely future direction of a price movment This approach assumes that security prices are determined solely by the interaction of market demand and supply and that prices tend to move in trends, and shifts in demand and supply cause trend reversals[iii]. Technical analysis uses various indicators which typically consist of price and trade volume transformations in order to identify a trend and forecast future price movements. In contrast, fundamental analysis aims at determining the long-term price target and does not concern itself with a study of price action[iv] and movement patterns.

Technical analysis can result in differing conclusions depending on the specific indicators or approach that is utilized, and while widely studied and practiced is still surrounded by some controversy. For example, the concept of a support level is extensively utilized in technical analysis as a price level at which a downward price movement tends to stop and reverse. However, no underlying mechanism has been previously identified for the formation of a support level and whether it will successfully hold.

Therefore, it would be desirable to develop a security pricing method that combines the strengths of fundamental analysis and its use of historical and projected data about a security together with the strengths of technical analysis in the form of charts and indicators. Such a method would use historical security data and optionally projected data as input into a security pricing model, which in turn would generate target price, support level, and price movement indicators for a security. In doing so this method can evaluate current security prices and anticipate future price movements while yielding further insight into the underlying mechanisms that may be responsible for the observed price movements and chart patterns.

Dynamics of Price Movement

The expected price movement and target price for a security pursuant to an event can be estimated by applying a time derivative to the price equation[iv], as follows:

$$P = EPS * PE \tag{01}$$

$$\Delta P = \Delta EPS * PE_0 + EPS_0 * \Delta P \tag{02}$$

$$P_T = P_0 + \Delta P \tag{03}$$

where ΔP represents the expected change in price resultant from a change in EPS or PE ratio at time t; P_0 and EPS_0 and PE_0 represent starting values for Price, EPS, and PE at a stable price point immediately preceding the event; and P_T is the target price.

The time derivative approach can be extended into a more general method by applying a conservation of capital principal. Market Capitalization (MC) represents the intrinsic capital or investment value of a security as a product of the total number of outstanding shares (S) and the share price, that is:

(04)
$$MC = S * P$$

In this manner, the share price acts as a unit of capital investment in the security. A positive event, such as a rise in earnings, results in an infusion of new investment into the security as buyers purchase shares of the security at a higher price level. The amount of new investment (I) generated by the onset of an event is equal to the change in market capitalization of the security, that is:

(05)
$$I = \Delta MC = S * \Delta P$$

A conservation principal may be defined stating that the change in market capitalization of a security must equal the amount of new investment flowing into the security. Such investment occurs when buyers purchase shares of a security at a higher price than the seller's cost basis, (the original purchase price paid by the seller to acquire the shares). Assuming a stable initial price and a single event, the seller's cost basis would equal the security's trading price prior to the onset of the event, whereas the buyer's cost basis would be the purchase price at a point past the onset of the event. The amount of new investment can be measured by adding individual contributions from each trade transaction completed in the aftermath of the event. Assuming N transactions have been completed at time t measured from the onset of an event, each involving s(n) shares, the amount of new investment can be measured by adding the incremental new investment from each transaction, as follows:

(06)
$$I(t) = \sum_{n=1}^{N} \left(s(n) * \Delta P_n\right)$$

where

(07)
$$\Delta P_n = P_{buyer\,cost} - P_{seller\,cost}$$

is the difference between the buyer and the seller's per share cost basis, and $s(n) * \Delta P_n$ is the incremental new investment for transaction n.

A support ratio indicator can be defined and measured by dividing the amount of new investment at time t by the expected change in market capitalization, as follows:

(08)
$$Support\ Ratio\ (t) = \frac{\sum_{n=1}^{N} \left(s(n) * \Delta P_n\right)}{S_{Total} * \Delta P}$$

As the support ratio reaches one the amount of new investment equals the change in market capitalization, satisfying the conservation principal, and a fully supported price level is established for the target price. A low support ratio indicates a lack of adequate new investment, while support ratios exceeding one indicate over-investment.

A divergence indicator can be defined and measured as the ratio of remaining price spread (ΔP_T) over price at time t, as follows:

(09)
$$Divergence\ (t) = \frac{\Delta P_T}{P} = \frac{P_T - P}{P} = \frac{P_T}{P} - 1$$

where price spread is measured as the difference between the target price and observed price. Divergence moves towards zero as price approaches the target price, and a fully supported price level is established. Divergence is an indicator of the price appreciation potential of a security.

The time elapsed from an event's onset until a fully supported price level is reached is referred to as the event time horizon (ΔT). For the special case of a linear price movement and constant trade volume, the event time horizon may be estimated as a ratio of the elapsed time over the measured support ratio, as follows:

(10)
$$\Delta T = \frac{t}{Support\ Ratio\ (t)}$$

with the value refined after each successive observation. The expected price at time t may also be estimated for this special case by multiplying the expected price change (ΔP) for the event by the measured support ratio, and adding the result to the starting price, as follows:

(11)
$$Expected\ Price\ (t) = P_0 + \Delta P * Support\ Ratio\ (t)$$

where the expected price reaches the target price as the support ratio reaches one. Together, the target price and the expected price form a price channel or an acceptable price range for the security.

Using the conservation principal the remaining investment required at time t in order to reach a fully supported price level may be measured, as follows:

(12)
$$I(t) = S * \Delta P_T$$

and an investment ratio may be defined as the remaining investment required per share as a multiple of the current share price, as follows:

(13)
$$Investment\ Ratio\ (t) = \frac{\Delta P_T}{P}$$

where the investment ratio is an indicator of the expected rate of investment in a security. A comparison to equation [09] reveals that Divergence is in effect the investment ratio of the security.

Treatment of Consecutive Events

The aforementioned approach may be further extended to cover multiple consecutive events for both isolated and overlapping event time horizons. For a single isolated event, as the support ratio reaches one, the event's life cycle completes with the expected price change dropping to zero and a new support level materializing at the projected target price. This support level forms a stable starting price (P_0) for a subsequent event and all indicators are reset to their starting values as a new cycle repeats. As such, an additive method may be used for combining multiple consecutive and isolated events and determining target prices.

For the case of multiple events with overlapping event time horizons, a similar aggregation method may be used. A common treatment is to calculate the expected price change for a new event in isolation using the aforementioned process. The expected price change is then added to the preceding event's target price. Since the target price is reset in the midst of the preceding event's life cycle, the expected price change and investment indicators now include contributions from multiple events.

A money flow indicator (MF) may be defined as an extension of the investment indicator with the money flow indicator spanning multiple events, as follows:

$$MF(t) = \sum_{n} [s(n) * \Delta P_n] \quad (14)$$

While the investment indicator is reset to zero at the completion of each event's life cycle, the money flow indicator operates continuously and captures the incremental investment flow from a select starting time. Sudden shifts in the direction and size of money flow represent changes in investor sentiment and require careful consideration by a prospective investor as they may signal a change in momentum.

Market Dynamics in Action

The Market Dynamics method has been applied to securities listed on the New York Stock Exchange and NASDAQ. The implementation requires application of several estimation techniques to measure the required input data elements such as PE values, new investment amounts, and event time horizons.

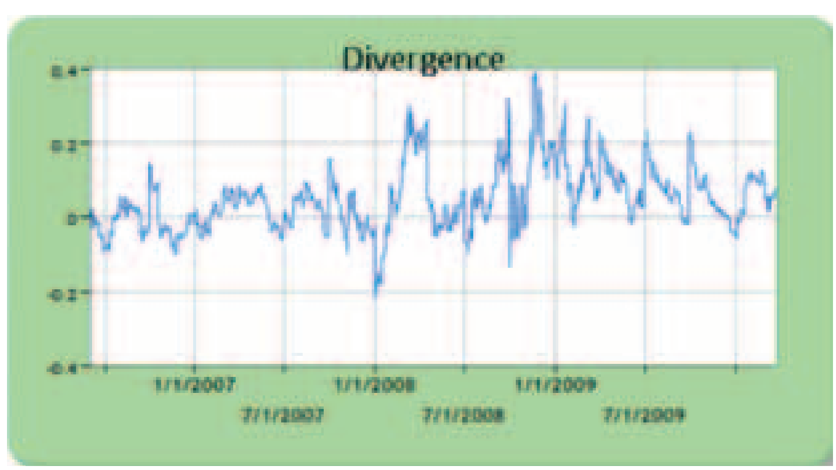
Figure 1 depicts the price channel chart for shares of Google for the period between June 2006 through to March 2010. The price channel indicator overlays the time series charts for target price, expected price, and the market price of a security. Point markers are also used to note fully supported price levels. When the price falls outside the price channel, a potential disparity exists between the current security price and its anticipated capitalization support. This may represent either an over-evaluation, as is the case with higher observed market prices above the channel, or otherwise an under-evaluation of the security below the channel.

The period between April 2009 and December 2009 represents an ascending channel for Google. It immediately follows a strongly supported price level, established and validated during the period from January 2009 through March 2009, as indicated by the presence of multiple support markers on the chart near the $370 price level. The ascending channel spans three consecutive earnings events represented by a stepped movement of the target price line on the chart. At the same time, the expected price moves gradually towards the target price as new investments continue to stream in. The price reaches the target price line in January 2010 and a new supported price level is established and later validated in March as observed by the subsequent price support markers on the chart. During December 2009, the security

Figure 1
Price Channel for Google, June 1, 2006 to March 25, 2010

Source: Market Dynamix

Figure 2
Divergence for Google, June 1, 2006 to March 25, 2010



Source: Market Dynamix

price moved away from the expected price line and eventually exited the price channel leading to a subsequent price correction in the first part of 2010.

Figures 2 and 3 present the corresponding divergence and investment charts for the same time period. The divergence indicator displays the potential apprecia-tion opportunity for the security and fluctuates with the level of investment flow, changes in target price, and market price for the security.

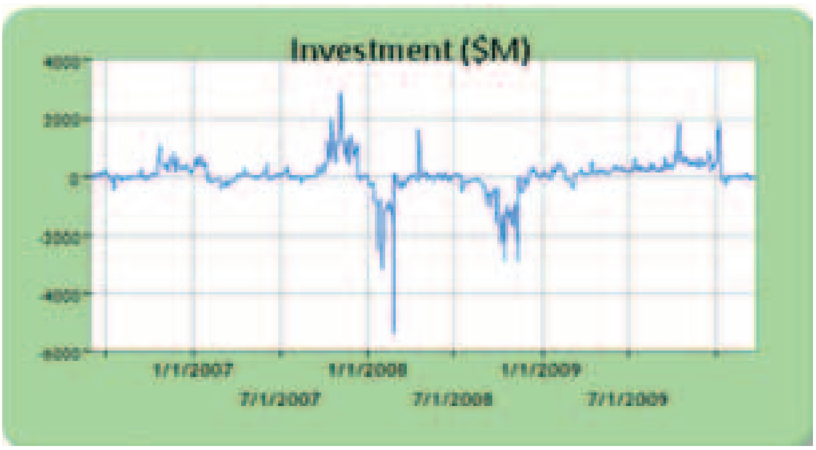
Figure 4 represents the money flow chart for Google. It shows a perceptible drop starting around January 1, 2008 due to the severe economic downturn. The money flow indicator represents investor sentiment and may be used to anticipate trend changes. A rising money flow trend may be observed from December 2008 through December 2009 preceding and overlapping the previously highlighted ascending channel.

The Potential for Market Dynamics

Market Dynamics presents a new approach to measuring and forecasting the price movement for traded securities and identifying their support levels, with the potential to leverage and partially bridge the divide between fundamental and technical analysis methods. The method can be applied to individual securities as well as related aggregates such as industry, sector, exchange traded indices or funds. When combined with a decision support system, Market Dynamics can be used as an investment strategy tool that lists securities with the greatest price appreciation opportunity for a selected investment style.

The application of Market Dynamics to the study of chart patterns can provide sought after insight into the underlying price movement mechanisms. Additional refinements and extensions of Market Dynamics are possible and desirable. For example, while the approach appears to work well with most securities further refinements are required for treating start-up and non-profitable companies as well as wide PE swings that may result in larger than anticipated price movements. **IFTA**

Figure 3
New Investment for Google, June 1, 2006 to March 25, 2010



Source: Market Dynamix

Figure 4
Money Flow for Google, June 1, 2006 to March 25, 2010

Source: Market Dynamix

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Some Mathematical Implications of the Original RSI Concept: Empirical Interpretation and Consequences for Technical Analysis (MFTA Research)

by Pavlos Th. Ioannou

Abstract

Keywords: *RSI, exact –RSI, Relative Price Activity (RPA©), the H-function© of RSI, support zones, resistance zones, relativistic phenomena, the unique mathematical relation between ROC and the RSI.*

The purpose of this paper is to study the logical implications of the original RSI concept. Towards this objective, the paper develops a simple mathematical model on the basis of which the exact meaning of RSI is derived and explained. This is quantified by the exact – RSI and it is shown that the RS ratio plays no role in its formation. The exact-RSI should be distinguished from the RSI currently in global use, which is the result of an exponential smoothing of the exact-RSI.

Within the framework of its mathematical model, the paper makes use of a concept (introduced elsewhere), referred to as the Relative Price Activity Index (RPA) and demonstrates the existence of a unique relation between the exact-RSI and the ROC oscillator. The main findings of the analytical work presented in this paper (with obvious consequences for technical analysis and technical trading) include:

(a) The exact-RSI (and therefore the smoothed RSI currently in use), cannot on its own identify successfully overbought/oversold conditions in a systematical manner. It is demonstrated that such conditions could objectively be identified and assessed only by considering both the exact RSI and RPA.

(b) In any market, the RPA index sets the natural upper and lower boundaries within which the ROC oscillator may move. Therefore, as the ROC moves towards these natural boundaries the probability to reverse its trend increases. It increases substantially when the value obtained by the ROC oscillator is very close to the prevailing value of the RPA which is the mathematical limit of the ROC oscillator.

(c) The current value of the ROC compared with certain critical levels of RPA along with the prevailing value of the exact-RSI, yields information that may improve our technical understanding of the state of a market. In addition, such an exercise may provide an insight as to the possible direction of the market in the immediate future.

Within the above context the paper underlines the relativistic character of the overbought/oversold concept and explains why the analytical framework it presents renders theoretical support to various empirical reservations, expressed in the literature on the RSI, concerning the ability of this Index to identify overbought/oversold zones. It is of particular importance that the paper derives formally the "point of reference" on the basis of which overbought–oversold zones should be assessed and explains why the RPA may generate support and resistance zones for the ROC oscillator. It is the power of the underlying relativistic phenomenon that will determine the reaction of the market and the strength of this reaction, i.e. whether the reaction is going to be a temporary correction or a sharp correction followed by a drastic reversal.

Introduction

The theory of the Relative Strength Index (RSI), with the relevant techniques and applications as developed by J. Welles Wilder Jr. in 1978, is probably one of the most important breakthroughs in the effort to quantify traditional bar-reading techniques of classical trend analysis. Its purpose is to make the visual readings of chart trend analysis more objectively understood, by "summarizing" price activity shown on bar-charts in terms of uniquely determined numbers. As wisely put by J. Welles Wilder Jr., "the Relative Strength Index is a tool which can add a new dimension to chart interpretation when plotted in conjunction with a daily bar chart"[i]. It is not a substitute for it.

Since the publication of the classic book by J. Welles Wilder, Jr., *New concepts in Technical Systems*, the Relative Strength Index became one of the most popular momentum oscillators used by traders. Indeed, "so popular that almost every charting software package and professional trading system anywhere in the world has it as one of its primary indicators"[ii].

The above global acceptance of the RSI techniques is clearly related to its perceived practical effectiveness. The other major reasons behind the rapid proliferation and popularity of the Relative Strength Index and relevant techniques, are well documented and discussed by C. D. Kirkpatrick and J. R. Dahlquist[iii].

At the same time, the literature on RSI was flourishing. This is evidenced by the brief bibliography presented at the end of this paper, which is only a small sample of relevant literature. It includes occasional reservations regarding the ability of the RSI to identify overbought/oversold zones and therefore, to preemptively signal reversals and reactions to trends. However, most of the work done and published is related to the further development (mathematically and/or otherwise) of its applications mainly for technical trading. Therefore, there has been no systematic effort to analyse the gist of the concept, per se, in order to exploit its potential analytical power and fully reveal and establish its quantitative and other implications.

It is the purpose of this paper to fill this gap. It employs the method of deriving logical implications from first principles, in this case those related to the original concept of the RSI, and by using simple mathematical techniques, the analysis presented here arrives at various analytically meaningful results. Then the paper proceeds to discuss practical implications of these results and to relate when necessary, some of the theoretical findings of the analysis presented to various empirical reservations in the literature, regarding the ability of the RSI to identify overbought/oversold zones.

The simple mathematical model for the study of the RSI and its properties

As outlined above, the objective of this paper involves the derivation of certain implications of the original RSI concepts and the study of their properties. It is based on a simple mathematical model which is explained in what immediately follows.

To calculate the RSI, one needs to consider discrete time series of closing prices, $P(t)$ where,

$$t = 1, 2, 3 \ldots, T\text{-}N, T\text{-}N+1, \ldots, T\text{-}1, T \quad (2.1)$$

(a) T is the time at which the current closing price, $P(T)$, is referred to, say today. However it may refer to the time at which a specific measurement of RSI (or any other indicator) is related to.

(b) N is the number of closing prices (including current one) that are required for calculating RSI (or any other oscillator).

(c) $T\text{-}N+1$, is the time from which we start calculating RSI in order to obtain a result requiring the consideration of N closing prices (including the current one. Therefore, $P(T\text{-}N+1)$ is the starting closing price or the reference closing price for all relevant calculations.

Clearly when we refer to an RSI measurement we mean RSI (t, N), i.e. RSI measured at time t, over N closing prices.

Given the time series $P(t)$, with t as defined in (2.1), one may derive the following differences between successive closing prices:

$$\Delta P(t, t\text{-}1) = P(t) - P(t\text{-}1), \; t \geq 2 \quad (2.2)$$

So, to calculate RSI (T, N), one has to set the reference price at $P(T\text{-}N+1)$ and derive above differences up to $P(T)$, as follows:

$$(1)\; \Delta P(T\text{-}N+2, T\text{-}N+1) = P(T\text{-}N+2) - P(T\text{-}N+1) = m(1) \quad (2.3)$$

$$(2)\; \Delta P(T\text{-}N+3, T\text{-}N+2) = P(T\text{-}N+3) - P(T\text{-}N+2) = m(2) \quad (2.4)$$

$$(3)\; \Delta P(T\text{-}N+4, T\text{-}N+3) = P(T\text{-}N+4) - P(T\text{-}N+3) = m(3) \quad (2.5)$$

$$(p)\; \Delta P(T\text{-}N+p+1, T\text{-}N+p) = P(T\text{-}N+p) - P(T\text{-}N+p\text{-}1) = m(p) \quad (2.6)$$

$$(N\text{-}1)\; \Delta P(T, T\text{-}1) = P(T) - P(T\text{-}1) = m(N\text{-}1) \quad (2.7)$$

The general form of writing the above differences is given by:

$$m(a) = \Delta(T\text{-}N+j+1, T\text{-}N+j) = P(T\text{-}N+j+1) - P(T\text{-}N+j) \quad (2.8)$$

In every case, the value of a, in $m(a)$, is arrived at by subtracting $T\text{-}N+1$ (i.e. the time at which reference closing price is set) from $T\text{-}N+j+1$ (i.e. the time related to the closing price for which its difference, from the previous closing price, is being defined). So,

$$\alpha = T\text{-}N+j+1 - (T\text{-}N+1) = j \ldots \quad (2.9)$$

In the case of the difference between the last closing price and its previous one, the following holds true:

$$m(a) = P(T) - P(T\text{-}1) = m(N\text{-}1) \ldots \quad (2.10)$$

because

$$a = T - (T - N + 1) = N - 1 \ldots \quad (2.11)$$

Further the model explicitly adopts the following assumptions:

Assumption (1) $P(t) > 0$ (2.12)

In other words, the price of a marketable stock is never zero.

Assumption (2) In every successive group of N closing prices (N of reasonable length, say ≥4), there is always at least one ΔP, as define by (2.3) to (2.7), which is not zero. In other words, the time series $P(t)$ refers to stocks with evidence of some trending activity, including activity within sideway ranges.

Preliminary formulations

Each of the differences defined by (2.3) to (2.7) quantifies the **net effect** of what is known in technical analysis as daily price activity. For the purposes of our analysis we make use of the following definitions:

Definition (1) Daily price activity, DPA (t) is the absolute value of the difference between $P(t)$ and $P(t\text{-}1)$, as follows:

$$DPA(t) = |P(t) - P(t\text{-}1)| \quad (2.13)$$

When DPA needs to be stated relative to a reference closing price, it is written (by implication of (2.7) and (2.8) as:

$$DPA(T\text{-}N+j+1)) = |P(T\text{-}N+j+1) - P(T\text{-}N+j)| = |m(j)| \ldots \quad (2.14)$$

Since DPA is an absolute value it is always non-negative. However, by implication of Assumption (2) it is possible to obtain (sometimes), a zero value, i.e.

$$DPA(t) \geq 0 \ldots \quad (2.15)$$

Definition (2) Total Price Activity (over N successive closing prices starting from the closing price generated at session $T\text{-}N+1$ up to and including the closing price of session T), denoted by TPA (T, N), is the sum of all Daily Price Activities derived from the N sessions considered. It is calculated as follows:

$$TPA(T,N) = \sum_{j=1}^{N-1} |P(T\text{-}N+j+1) - P(T\text{-}N+j)| = \sum_{j=1}^{N-1} |m(j)| \qquad 2.16$$

By implication of Assumption (2), TPA (T, N) has to be always positive i.e.,

$$TPA (T, N) > 0 \qquad 2.17$$

Definition (3) Net Price Activity, over N successive closing prices starting from the closing price generated by session T – N + 1 up to and including the closing price at session T, is the sum of the differences between the N successive closing prices considered. It is denoted by NPA (T, N) and calculated as follows:

$$NPA (T, N) = \sum_{j=1}^{N-1} \{P(T\text{-}N+j+1) - P (T\text{-}N+j)\} = \sum_{j=1}^{N-1} m(j) \qquad 2.18$$

Unlike TPA (T, N), the NPA (T, N) can be positive, negative or zero depending on the direction overall price activity is moving to form P(T, N), the ending closing price. The formulation presented, allows at this stage the derivation of a rather obvious but still important statement.

STATEMENT (A) Net price activity, NPA (t, N) is always equal to the difference of the reference closing price P (t-N+1) from closing price P(t), i.e.

$$NPA (t, N) = P(t) - P (t\text{-}N+1) \qquad 2.19$$

To understand why (2.19) always holds true, one only needs to look at the definition of NPA and then apply (2.18) to sum up the differences from (2.3) to (2.7). All closing prices other than P(t) and P(t-N+1) should cancel out (telescoping cancellation) and the end result will be as shown by (2.19).

As will be explained, **this simple result provides, among other analytical uses, a unique mathematical link between the RSI and other technical indicators, such as the Rate of Change (ROC)**. For the purposes of this model ROC is defined as follows:

Definition (4) The Rate of Change ROC (t, N) of P(t) relative to closing price, N sessions ago, P(t-N+1), measures the amount of change generated by the price activities of the N sessions considered that caused the starting closing price to change from P(t-N+1) to P(t), as a ratio of the starting closing price. It is calculated[iv] on the basis of the following formula:

$$ROC = \{ P_{today} - P_{N\ periods\ Ago}) / P_{N\ periods\ ago} \} \times 100 \ \ldots \qquad 2.20$$

Dropping the percentage transformation in (2.19) and re-writing it using the notational convention of this paper, we end up with the following:

$$ROC (t, N) = \frac{P(t) - P(t-N+1)}{P(t-N+1)} \ \ldots \qquad 2.21$$

Substituting (2.19) into (2.21), the following will hold true:

$$ROC (t, N) = \frac{NPA(t,N)}{P(t-N+1)} \ \ldots \qquad 2.22$$

Definition (5) Relative Price Activity[v], denoted by RPA (t, N), is the ratio of TPA(t, N) to the reference price, P(t-N+1). As such it measures the intensity of price activity that took place over the period considered as a fraction of the reference price. It is calculated on the basis of the following formula:

$$RPA (t, N) = \frac{TPA(t,N)}{P(t-N+1)} \ \ldots \qquad 2.23$$

RPA (t, N) is always positive and there are strong theoretical reasons[vi] that allow us to predict that most of the time it should be less than one. Indeed when it is higher than one, the same theoretical reasons predict that strong movements are taking place in the market followed by similarly strong reactions. Indeed, it is also predicted that during periods of smooth price activity (both down trending and up trending conditions, with non violent corrections), the RPA must be rather small.

The Ups (U) and Downs (D) convention within the notational context of this model

Most of the literature on RSI discusses analytical issues of the index in terms of "Ups" and "Downs", denoted respectively by U and D. To facilitate further discussion and analysis towards the objectives of this paper it is necessary to align the "Ups" and "Downs" convention with the notational approach previously developed.

The differences ΔP (t, t-1) in (2.2) and consequently the differences m(j) in (2.3) to (2.7) can be positive, negative or zero. Suppose that we consider N-1 such differences derived for a time series of N closing prices from P(t – N+1) to P(t). We can always group all the positive differences in a group denoted by U and all the negative differences, in another group denoted by D. Let us start from m(1), i.e. the difference:

$$P (t - N +2) - P (t - N + 1) .$$

If this is positive, it is identified as U(1). If it is negative is identified as D(1). If it is zero, it is neglected. Therefore group U and group D are constructed on the basis of the following rule:

$$\text{If } m (j) \neq 0 \text{ then } m (j) = \begin{cases} U(k), \text{ if } m(j) > 0 \\ -D(f), \text{ if } m(j) < 0 \end{cases} \ \ldots \qquad 2.24$$

where:

$$k = 1, 2, \ldots K. \ \ldots \qquad 2.25$$

$$f = 1, 2, \ldots. F \ \ldots \qquad 2.26$$

and

$$K+F \leq N\text{-}1 \ \ldots \qquad 2.27$$

depending on how many differences $m(j)$ are identified to be equal to zero.

Furthermore, each time a $U(k)$ is identified, on the basis of the rule, denote the corresponding positive $m(j)$ by $m(j,k)$. Similarly, each time a $D(f)$ is identified, denote corresponding negative $m(i)$ by $m(i, f)$.

Adopt now the following definitions:

$$\text{(A)} \quad U(t, N) = \sum_{k=1}^{K} m(k) = \sum_{k=1}^{K} m(j, k) \quad \ldots \tag{2.28}$$

Because of (2.24), $U(K) > 0$. Therefore,

$$U(K) = |U(K)| \quad \ldots \tag{2.29}$$

and the same holds true for $m(j, k)$.

So, (2.28) may be rewritten as:

$$U(t, N) = \sum_{k=1}^{K} U(k) = \sum_{k=1}^{K} m(j, k) = \sum_{k=1}^{K} |m(j, k)| = \sum_{k=1}^{K} |U(K)| \quad \ldots \tag{2.30}$$

$$\text{(B)} \quad -D(t, N) = \sum_{f=1}^{F} -D(f) = \sum_{f=1}^{F} m(i, f) \ldots \tag{2.31}$$

Because of (2.24), $-D(f) < 0$, being equal to a negative $m(i)$. Therefore the following holds true:

$$|-D(f)| = -[-D(f)] = D(f) \ldots \tag{2.32}$$

and the same holds true for $m(i, f)$.

So, (2.31) may be rewritten as:

$$D(t, N) = -[-D(t,N)] = -\sum_{f=1}^{F} [-D(f)] = \sum_{f=1}^{F} |-D(f)| = \sum_{f=1}^{F} D(f) \ldots \tag{2.33}$$

Of course the originator of the Ups and Downs conversion is J. Welles Wilder Jr. This convention appeared in his classic *New concepts in Technical Trading Systems*[vii]. In that context, UP is "the sum of the UP closes for the previous fourteen days"[viii]. This is identical to expressions (2.30) above, when N is set at fifteen days (or sessions), from which fourteen, $m(j)$ differences are derived. Some of them are positive, representing the Up closes, as defined in (2.24) and others are negatives, representing the Down closes, also defined in (2.24). The "sum of the Down closes"[ix], is identical to expression (2.33) above. Furthermore, one may write:

$$1)\quad TPA(t, N) = \sum_{j=1}^{N-1} DPA(j) = U(t, N) + D(t, N) \ldots \tag{2.34}$$

$$2)\quad RPA(t, N) = \frac{TPA(t,N)}{P(t-N+1)} = \frac{U(t,N)+D(t,N)}{P(t-N+1)} \ldots \tag{2.35}$$

$$3)\quad ROC(t, N) = \frac{NPA(t,N)}{P(t-N+1)} = \frac{U(t,N)-D(t,N)}{P(t-N+1)} \ldots \tag{2.36}$$

Equation (2.34) holds true because it is derived by substituting (2.30) and (2.33) into (2.16), bearing in mind the rule defined by (2.34). Equation (2.35) holds true because it results from the substitution of (2.32) into the definition (2.23). Equation (2.36) is arrived at by noting that NPA (t, N) is the sum of all $m(j)$. But, because of (2.28) and (2.31), the difference $U(t, N) - D(t, N)$ is by implication of (2.24) the sum of all $m(j)$ as well. Hence, this difference is equal to NPA (t, N).

The implications of the original RSI concepts: The exact RSI, its properties and the unique mathematical relation between RSI and ROC

J Welles Wilder Jr in his classic and influential book, *New Concepts in Technical Trading Systems* introduces RSI, in the following manner:

"The equation for the Relative Strength Index, RSI, is:

$$RSI = 100 - \left[\frac{100}{1+Rs}\right]$$

$$RS = \frac{\text{Average of 14 days closes UP}}{\text{Average of 14 days closes DOWN}}$$

For the first calculation of the Relative Strength Index, RSI, we need the previous fourteen days closing prices"[x].

Derivation of the implications of the original RSI concepts

The above statement and relevant formulation comprises the gist of the original RSI concept. By implication of expression (2.3) to (2.8) and as explained previously, to get N-1 "closes up" or "closes down", one needs N closing prices, i.e. observations for N sessions. So, to get fourteen prices and the resulting "closes up" or "closes down", N has to be set equal to fifteen. Indeed, the view that "to compute a fourteen-day RSI, you must first collect fourteen days of closing prices"[xi] is not valid. The fourteen-day RSI utilizes fifteen days closing prices to obtain fourteen changes between the successive fifteen closing prices. Therefore, making use of (2.28) and (2.31), one may re-write the original definition as follows:

$$RS = \frac{\text{Average of 14 days closes UP}}{\text{Average of 14 days closes DOWN}} = \frac{\left(\frac{1}{14}\right).U(t,15)}{\left(\frac{1}{14}\right).D(t,15)} = \frac{U(t,15)}{D(t,15)} \tag{3.1}$$

Therefore,

$$1 + RS = 1 + \frac{U(t,15)}{D(t,15)} = \frac{D(t,15)+U(t,15)}{D(t,15)} \quad \ldots \tag{3.2}$$

The RSI equation given above many be rearranged as follows:

$$RSI = 100 - \left[\frac{100}{1+RS}\right] = 100\left[1 - \frac{1}{1+RS}\right] = \frac{1+RS-1}{1+RS} = \frac{RS}{1+RS} \ldots \tag{3.3}$$

Substituting into (3.3) eq. (3.2) and eq. (3.1) and dropping the percentage transformation, the RSI equation becomes:

$$RSI = \frac{RS}{1+RS} = \frac{\dfrac{U(t,15)}{D(t,15)}}{\dfrac{U(t,15)+D(5,15)}{D(t,15)}} = \frac{U(t,15)}{U(t,15)+D(t,15)} \tag{3.4}$$

Therefore substituting into (3.4), eq. (2.32) we end up with:

$$RSI\ (t,15) = \frac{U(t,15)}{TPA(t,15)} \tag{3.5}$$

Equation (3.5) above for RSI $(t, 15)$ is a direct logical implication of the original RSI concepts and, indeed, describes exactly what RSI is. Generalizing for N periods (3.5) is written as:

$$RSI\ (t, N) = \frac{U(t,N)}{TPA(t,N)} \tag{3.6}$$

The formulation (3.6) allows for the following statement.

STATEMENT (B) The original RSI concepts imply that the exact RSI (t, N) is the ratio of $U\ (t, N)$ to TPA (t, N) i.e., it measures the contribution of total positive changes between the successive closing prices observed from the starting closing price $P(t-N+1)$ to the current one $P(t)$, both included, to the Total Price Activity (TPA) of the period considered.

It should be noted that the exact RSI is independent from the ratio RS. This term is not necessary in order to construct the definition of RSI (t, N).The definition of RSI is simply given by expression (3.6) and described by Statement (B). Hence, by implication of (3.6), the RS ratio contributes nothing into the relevant calculation process. On the contrary, the use of RS imposes a certain constraint in the mathematical use of the concept. It requires specifically, in addition to the two assumptions stated above, that in the period considered there should be at least one ΔP which is negative.

Therefore, to say "RSI measures the ratio of average price changes for closes up to average price changes for closes down and then normalizes the calculation to **be** between one and 100"[xii] is clearly the result of a misunderstanding.

The following are some general and well known properties of the RSI:

(a) $$0 \le \text{exact RSI} \le 1 \tag{3.7}$$

A zero value is obtained when the market is continuously down trending i.e., when there is no positive change during the period considered and all observed changes are negative. If the opposite holds true, then RSI attains a value equal to one.

(b) When the exact RSI is equal to 0.5, the total up movements are equal to the total down moments, i.e.:

$$U\ (t, N) = D\ (t, N) \tag{3.8}$$

Therefore,

$$U\ (t, N) - D\ (t, N) = 0 \tag{3.9}$$

Expression (3.9) when combined with (2.36), implies that

$$ROC\ (t, N) = 0 \tag{3.10}$$

or in other words the current closing price $P(t)$ is just equal to the reference price for the relevant RSI evaluations $P\ (t- N+1)$.

The unique mathematical relation between RSI and ROC

One of the important outcomes of the study of the implications of the original RSI concepts, as carried out in this paper, is that it reveals the existence of a unique mathematical relation between the RSI and ROC oscillators.

Indeed, because of (2.34), the following is true:

$$D\ (t, N) = TPA\ (t, N) - U\ (t, N) \tag{3.11}$$

Substituting (3.11) into expression (2.36) one obtains the following:

$$ROC\ (t,N) = \frac{U(t,N)-[TPA(t,N)-U(t,N)]}{P(t-N+1)} = \frac{2U(t,N)-TPA(t,N)}{P(t-N+1)} \tag{3.12}$$

Because of equation (3.6), $U\ (t, N)$ may be written as

$$U(t, N) = TPA\ (t, N)\ \ RSI\ (t, N) \tag{3.13}$$

Substituting now (3.13) back into (3.12) one obtains:

$$ROC\ (t,N) = \frac{2U(t,N)-TPA(t,N)}{P(t-N+1)} = \frac{2RSI(t,N).TPA(t,N)-TPA(t,N)}{P(t-N+1)} = [2RSI\ (t,N)-1]\ .\ \frac{TPA(t,N)}{P(t-N+1)} \tag{3.14}$$

Remembering the definition for the Relative Price Activity (RPA) given by expression (2.23) and substituting this into the right hand side of (3.14), the following is established:

$$ROC\ (t, N) = [\ 2RSI\ (t, N) - 1]\ \ RPA\ (t, N) \tag{3.15}$$

This allows for the third statement of this paper.

STATEMENT (C) For any series of N successive closing prices, from $P\ (t-N+1)$ to $P(t)$, both included, the implied exact RSI (t, N) and ROC (t, N) are uniquely related to each other on the basis of the rule:

$$ROC\ (t, N) = H\ (t, N)\ .\ RPA\ (t, N) \tag{3.16}$$

where:

$$H(t, N) = 2RSI(t, N) - 1 \quad (3.17)$$

The H (t, N)©, will be referred to as the H-function© of RSI. It measures the rate at which the specific structure of price activity (reflected on RSI), transforms relative price activity RPA (t, N), into actual change in price P(t), relatively to P (t-N+1), the starting closing price with reference to which price activity is being studied. The following conclusions are the direct implications of Statement (C) and the mathematical forms of the way RSI (t, N) is uniquely related to ROC (t, N).

Conclusion (a)

For any series of N successive closing prices the value of RSI (t, N) determines **only the rate** at which price activity forming the N closing prices considered, is transformed into **actual change** in P(t) relative to the reference closing price P (t-N+1).

Conclusion (b)

However, the value of RSI (t, N) conclusively determines the direction of the above change (i.e. its sign), independently of RPA (t, N) because RPA (t, N) is always positive. The critical value of the H-function concerning this direction is zero. If this is the case, irrespective of how intense the price activity (and therefore how large the value of RPA (t, N)), the structure of the price activity does not induce an actual price change in P(t). This occurs when RSI (t, N) = 0.5.

Conclusion (c)

Price activity generates positive or negative price change in P(t), only when H (t, N) is above or below zero, respectively. However, when positive irrespective of how big the value of H (t, N) and therefore RSI, the resulting effect of the price activity will be *small*, if RPA (t, N) is low. The same holds true, if the H-function is negative.

Conclusion (d)

By implication of the above conclusions and to the extent that ROC (t, N) may be used for assessing overbought/oversold conditions, clearly the value of the RSI (t, N) on its own, cannot provide conclusive evidence on whether price activity is leading the market in to overbought/oversold conditions. For such evidence to commence becoming meaningful one needs constantly to assess the size of the RPA (t, N), because of expression (3.15), indicating that ROC is jointly determined by both RSI and RPA.

A note on the history of the subject

It is acknowledged at this stage, that equation (3.6) and the relevant explanation in Statement (B), appear in the literature on RSI twice. The first[xiii], was in a professional journal and the second in an academic working paper[xiv]. In both cases the objectives of the authors were not related to conceptual issues. Therefore, they have not carried out the kind of analysis presented in this paper.

On the other hand, it is clear that the demonstration of the existence of a unique mathematical relation between ROC and the exact-RSI and everything else related to this mathematical fact, are presented here for the first time. Therefore the underlying research, analytical work and relevant findings are all purely original. The same is true for the study of the quantitative implications of this relation which are presented in what follows.

Critical values of RPA, RSI and ROC: Their properties and a brief empirical investigation

The index of Relative Price Activity (RPA) has certain interesting and important properties; when properly understood, their quantitative implications may be effectively employed in practice as analytical benchmarks for assessing the state of a market. Consequently they are of benefit for both technical analysis and technical trading purposes.

The reasons behind the analytical properties of the RPA are mostly contained in the mathematical rule that uniquely relates ROC to RSI and RPA described by (3.16). When the RSI function attains various values from minus one (-1) to plus one (+1), the ROC attains values uniquely determined by the prevailing value of the RPA. Therefore RPA sets the boundaries of the values attainable by the ROC. Table 1, presents the values attained by the ROC when the RSI function is at certain critical values. Relevant calculations have been carried out, on the basis of (3.16) and (3.17).

Table 1

Critical values of (2RSI-1) and the values imposed to the ROC by the RPA

CASE	RSI	2RSI-1	ROC
1	1	1	RPA
2	0	-1	neg.RPA
3	0.5	0	0
4	(RPA+1)*0.5	RPA	RPA^2
5	neg(RPA+1)*0.5	neg.RPA	RPA^2
6	0.75	0.5	0.5*RPA
7	-0.75	-0.5	neg.RPA

Properties of the RPA

Carefully analysing each case presented on Table 1, one may derive the following properties of the RPA in relation to the determination of the ROC:

Property (1): The Relative Price Activity (RPA) sets the upper and lower limits of the values attained by the ROC, irrespective of RSI. This is a logical implication of cases (1) and (2) in Table 1. When the RSI function, (2RSI-1), reaches one (its upper boundary) the ROC is just equal to the prevailing RPA. **From the point of view of technical analysis, this purely mathematical property implies that this value of the RPA generates a resistance "zone" for the ROC. When the RSI function, (2RSI-1), reaches -1, (minus one), the negative of RPA generates a support "zone" for the ROC.**

Property (2): When the curve of the function of the RSI cuts the RPA line, then 2RSI-1=RPA and ROC=(RPA)^2. This is case (4) in Table 1. Such an event may occur only when the function of the RSI is positive, since the RPA is always positive.

Taking total differentials of expression (3.16.) one obtains:

$$dROC = H.\,dRPA + RPA.\,dH \quad \ldots \tag{4.1}$$

Dividing both sides of (4.1) by dt, one obtains the following rate of change over time:

$$\frac{dROC}{dt} = H\frac{dRPA}{dt} + RPA\frac{dH}{dt} \tag{4.2}$$

Therefore when the H function of RSI cuts RPA from below to above (this means that $\frac{dH}{dt}>0$), RPA has to be equal to H. Under these circumstances expression (4.2) implies:

$$\frac{dROC}{dt} = H\left(\frac{dRPA}{dt}+\frac{dH}{dt}\right) \tag{4.3}$$

The above is particularly meaningful from the point of view of technical analysis, because it allows one to draw almost unambiguous conclusions about prevailing conditions in the market and possibly, its immediate future, as follows:

(a) After the cut, the RPA is not decreasing: means that the ROC continues to increase (entered positive region anyway, because the H function of RSI may cut RPA only when $H>0$ i.e. $RSI>0.5$). The market is in a bullish state and most probably will remain so in the immediate future.

(b) After the cut, the RPA and the H–function are both increasing: This is a very bullish sign, when (and if) it occurs, because after the cut the ROC will probably be increasing at an accelerating pace.

(c) It should be noted that (a) and (b) are independent of any considerations about overbought/oversold conditions. Instead, the market, on its own, reveals its intentions through the observed state of $\frac{dH}{dt}$ and $\frac{dRPA}{dt}$. Under the conditions considered, they are both positive and continue to increase. However, good things do not last for ever. Eventually the power of the market will start to diminish, exhaust completely and put in place a reaction to the previous up trending move. But again, the intentions of the market will be shown. Either H or RPA will start to show weakness and attain a local maximum. Clearly the prevailing move is loosing steam. If both $\frac{dH}{dt}$ and $\frac{dRPA}{dt}$ turn negative, then a reaction is in operation. Similarly (a) and (b) also hold true (but to the opposite direction), when the H-function of the RSI cuts the RPA from above to below.

Some empirical evidence on how the exact RSI, the ROC and the RPA behave in historical markets

At this stage it is useful to consider empirically the way the RSI, the ROC, and the RPA behave in actual markets. The purpose is to acquire a general idea of the band of values obtained in real markets by the RPA, in order to understand how these **values relate to the range of values obtained by the RSI and the ROC**. This does not involve the statistical construction of globally valid bench marks. Given the state of market activity as far as the general trend is concerned, the RPA reflects how smoothly the trend develops. A smooth up trend with reasonable technical corrections is associated with low RPA values. Therefore, as noted previously, its value varies according to the structure of the overall market trend. So, establishing benchmarks is not relevant. Therefore no statistical tests are considered.

Towards the above objective we have investigated two groups of time series of closing prices; one for the period from August 1, 2007 to November 20, 2009 and one for the period from July 3, 2006 to December 31, 2007, generated by the following markets:

(a) New York Stock Exchange, by considering the indices DJI and S&P 500.

(b) Euronext Paris, by considering the CAC-40 index.

(c) London Stock Exchange, by considering the FTSE 100 index.

(d) Tokyo Stock Exchange, by considering the NIKKEI 225 index.

(e) Australian Stock Exchange, by considering the S&P/ASX All Ordinaries 500 Index.

The above slightly overlapping periods have specific characteristics. The first was a period of drastic price activity associated with the Global Financial Crisis. The second was a period of generally smooth up trending movements. The difference between them enhances the understanding of the implications of the properties of the RPA and the empirical validation of our argument. According to which, any given value of the RSI on its own and without consideration of the corresponding value of the RPA, cannot conclusively tell whether the market is entering into overbought/oversold zones.

In addition, it helps to empirically validate our theoretical prediction that under conditions of smooth trending, the RPA attains small values, irrespective of the magnitude of the RSI.

Summary of findings

For the calculation requirements of the above exercise we have used the formulae described by (2.35), (2.36) and (3.6) to calculate the RPA, ROC and RSI, respectively. N was set equal to fifteen. Then, the Excel Summary Statistics function was used, to derive mean, median, range, maximum and minimum values for each market indicator. Relevant results are presented on Tables 2, 3 and 4, for the first group of data.

Table 2

Maximum, minimum and Range of the exact-RSI on various International Indices for the period from August 1, 2007 to November 20, 2009.

	DJI	S&P 500	NIKKEI 225	CAC 40	FTSE 100	All Ords (ASX)	Average
Mean	0.5010	0.5027	0.4811	0.4934	0.5112	0.5107	0.5000
Median	0.5058	0.5096	0.4782	0.4911	0.5209	0.5067	0.5021
Range	0.8266	0.8092	0.9244	0.8330	0.8169	0.9450	0.8592
Min.	0.1106	0.1386	0.0712	0.0785	0.0906	0.0103	0.0833
Max.	0.9371	0.9478	0.9956	0.9115	0.9074	0.9553	0.9425

Table 3

Maximum, minimum and Range of the RPA on various International Indices for the period from August 1, 2007 to November 20, 2009.

	DJI	S&P 500	NIKKEI 225	CAC 40	FTSE 100	All Ords (ASX)	Average
Mean	0.1826	0.1991	0.2232	0.1986	0.1855	0.1714	0.1934
Median	0.1472	0.1532	0.1790	0.1711	0.1576	0.1474	0.1592
Range	0.5671	0.5724	0.8453	0.5818	0.5700	0.4057	0.5904
Min.	0.0613	0.0661	0.0816	0.0656	0.0586	0.0733	0.0677
Max.	0.6284	0.6385	0.9268	0.6474	0.6286	0.4790	0.6581

Table 4

Maximum, minimum and Range of the ROC on various International Indices for the period from August 1, 2007 to November 20, 2009.

	DJI	S&P 500	NIKKEI 225	CAC 40	FTSE 100	All Ords (ASX)	Average
Mean	-0.0047	-0.0051	-0.0106	-0.0072	-0.0021	-0.0040	-0.0056
Median	0.0016	0.0032	-0.0084	-0.0031	0.0071	0.0023	0.0005
Range	0.4425	0.4937	0.5274	0.3996	0.4224	0.3781	0.4440
Min.	-0.2467	-0.2750	-0.3161	-0.2479	-0.2491	-0.2199	-0.2591
Max.	0.1958	0.2187	0.2114	0.1517	0.1733	0.1582	0.1849

Tables 5 through 7 present the relevant analysis for the second group of data, corresponding to a period of a generally smooth, up trending move.

Table 5

Maximum, minimum and Range of the exact-RSI on various International Indices for the period from July 3, 2006 to December 31, 2007

	DJI	S&P 500	NIKKEI 225	CAC 40	FTSE 100	All Ords (ASX)	Average
Mean	0.5862	0.5728	0.5224	0.5479	0.5420	0.5738	0.5575
Median	0.5804	0.5793	0.5337	0.5533	0.5480	0.5734	0.5613
Range	0.6461	0.6298	0.7618	0.6467	0.6984	0.6574	0.6734
Min.	0.2404	0.2390	0.1543	0.2301	0.2152	0.2484	0.2212
Max.	0.8865	0.8688	0.9161	0.8768	0.9136	0.9058	0.8946

Table 6

Maximum, minimum and Range of the RPA on various International Indices for the period from July 3, 2006 to December 31, 2007

	DJI	S&P 500	NIKKEI 225	CAC 40	FTSE 100	All Ords (ASX)	Average
Mean	0.0793	0.0860	0.1138	0.1062	0.1003	0.0998	0.0976
Median	0.0663	0.0700	0.1082	0.0932	0.0818	0.0907	0.0850
Range	0.1545	0.1595	0.1642	0.2066	0.2362	0.1964	0.1862
Min.	0.0290	0.0378	0.0515	0.0445	0.0427	0.0472	0.0421
Max.	0.1835	0.1973	0.2157	0.2511	0.2789	0.2436	0.2284

Table 7

Maximum, minimum and Range of the ROC on various International Indices for the period from July 3, 2006 to December 31, 2007

	DJI	S&P 500	NIKKEI 225	CAC 40	FTSE 100	All Ords (ASX)	Average
Mean	0.0079	0.0065	0.0016	0.0057	0.0042	0.0100	0.0060
Median	0.0103	0.0106	0.0070	0.0100	0.0080	0.0142	0.0100
Range	0.1270	0.1362	0.2076	0.1718	0.1660	0.1843	0.1655
Min.	-0.0660	-0.0752	-0.1205	-0.0933	-0.0885	-0.0793	-0.0871
Max.	0.0610	0.0610	0.0871	0.0785	0.0776	0.1049	0.0783

Two concluding remarks:

(a) The low values of RPA obtained for the second period, render full empirical support to the theoretical prediction that low RPA is associated with smooth market movements.

(b) Comparing RSI values for the two periods, it can easily be observed that they are generally moving at similar levels. However the ROC is not, because of the substantial difference between the values of the RPA corresponding to the two periods. This finding fully confirms equations (3.16) and (3.17), as was expected.

The properties of the RPA in action: A brief empirical investigation of how the H-function of the RSI and the RPA interact to determine the ROC

It is necessary, and very interesting, to consider how the RPA properties explained above impose certain constraints on the way the market forms its ROC, through price activity, measured by the H-function of the RSI. For this purpose we have constructed an RSI, the H-function, RPA and ROC using data for the DJI index, for the period from June 30, 2009 to November 20, 2009.

Figure 1 depicts the movement of the DJI index over the period June 30, 2009 to November 20, 2009. The underlying price activity generates the RSI (and therefore the H-function), the RPA index and the ROC. These are presented in Figure 2 and Figure 3.

Figure 2 displays the H-function cutting the minus RPA from below to above at point A. On the same day, the DJI forms a trough shown by A_1 on Figure 1. This is the first bullish signal. (Note the dH/dt is sharply rising and the RPA line is almost flat). This signal is reconfirmed twice, when the H line cuts from below to above the line minus 0.5 RPA and then the line minus $(RPA)^2$. These cuts occur at points a and b respectively in Figure 2 and correspond to point b1 of DJI, in Figure 1. Note that these occur when the RSI is still below 0.5 and therefore the H-function is negative. Then, it cuts again from below to above the RPA at point B. This corresponds to point B1 on the DJI closing levels, shown in Figure 1. At the point of this intersection both curves have a positive slope. **This is very bullish.**

Indeed, as depicted in Figure 1, beyond this point the system enters into a sharp upward movement. It is sustained by a sharply increasing H-function and an almost flat RPA. This implies that the ROC is continuously increasing, as shown in Figure 3. **From the behavioural point of view these conditions have some interesting consequences.**

All market participants that have entered the market fifteen sessions ago (three weeks x five sessions per week, because N=15), find their trades profitable. So do those who have entered the market more recently. **Therefore, most of them are having no reason to consider closing their trades. Indeed some of them may be willing to increase positions.** This general attitude, along with possible new entrants in the market, supports the continuation of the uptrend. However,

Figure 1
DJI daily closing levels for the period June 30, 2009 to November 20, 2009

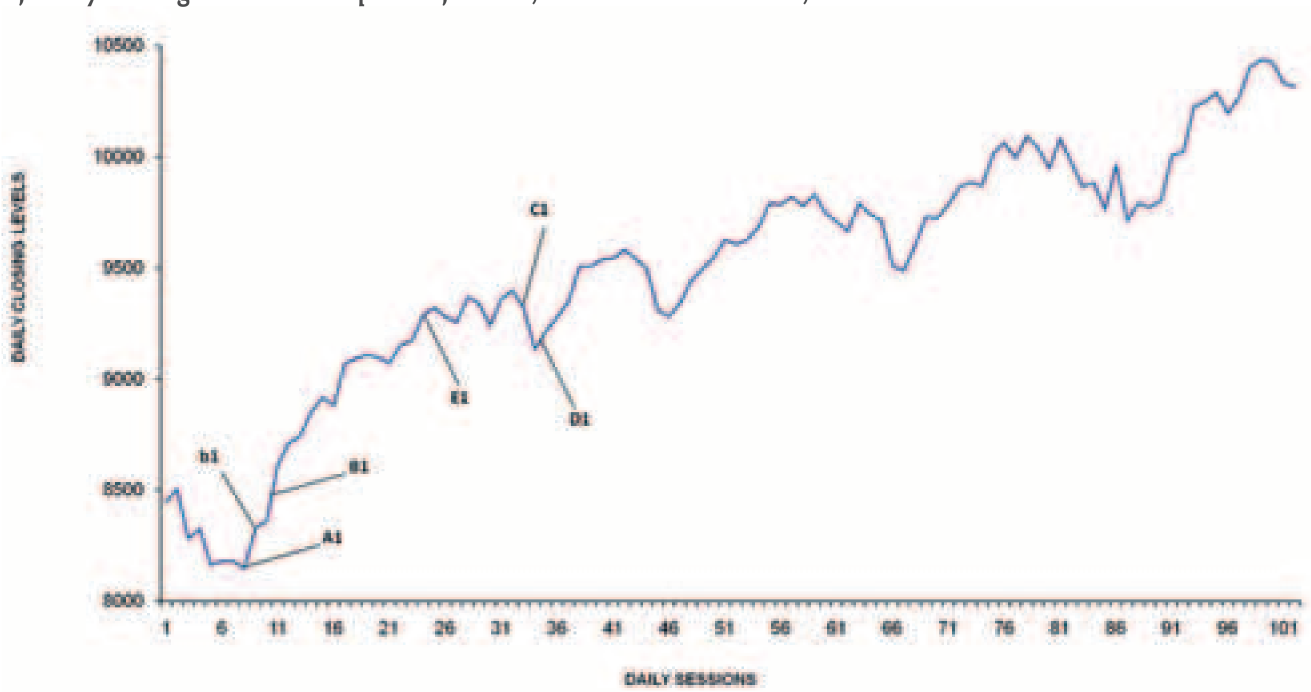
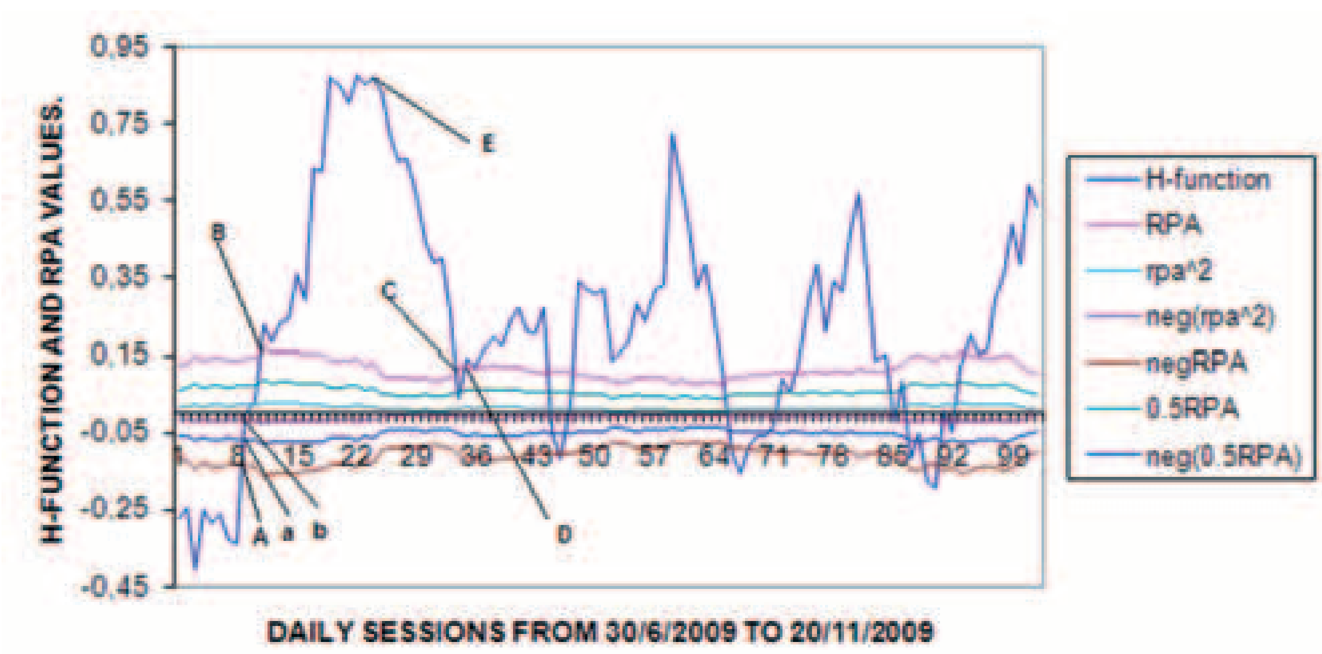


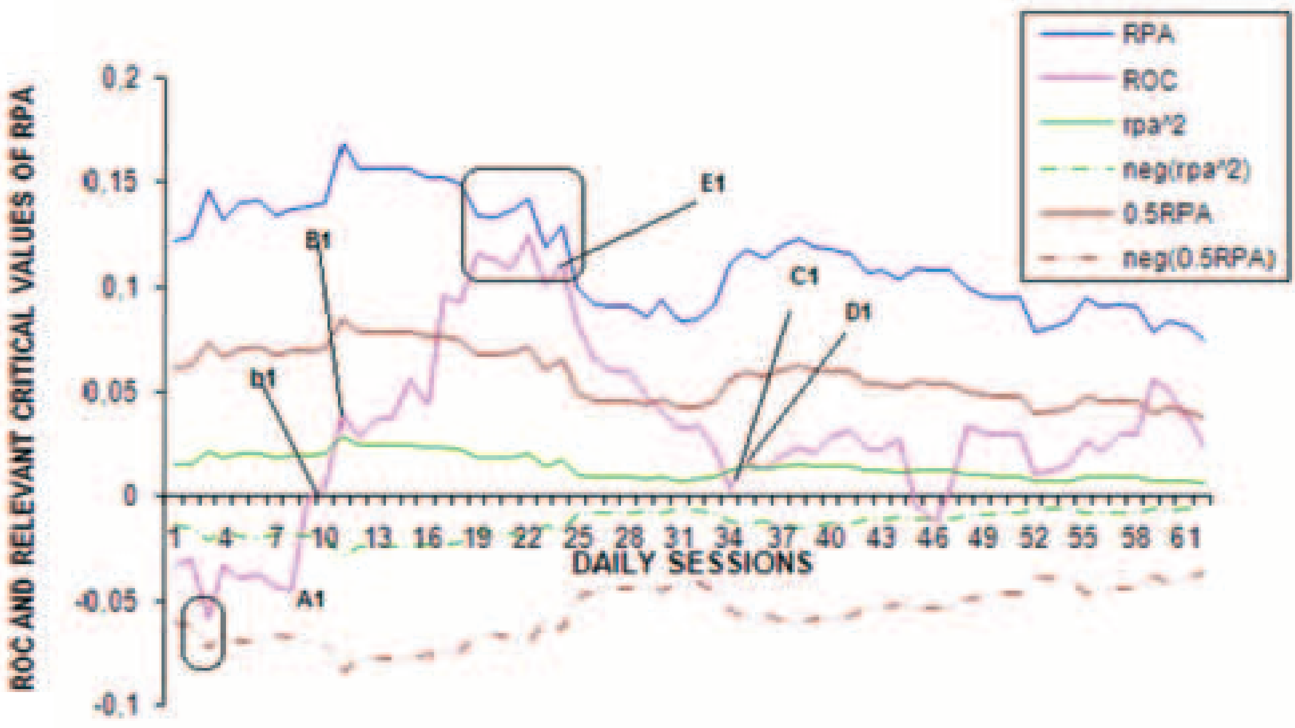
Figure 2
Using the movement of the H-function through the critical values of the RPA to assess the DJI price activity



this powerful uptrend inevitably, caused the ROC to reach its mathematical upper boundary. This is highlighted by the circled area which includes letter E1 in Figure 3. **It is clearly a resistance "zone", generated by a purely relativistic phenomenon.**

This was explained by the first property of the RPA presented previously. **The same property predicts the formation of a support "zone" when the H-function is negative and approaches -1 (minus one). This phenomenon, purely relativistic, is observed in the lower circled area in Figure 3.** Point E1 in Figure 3 corresponds to point E1 in Figure 4 and point E in Figure 2. It is the beginning of some distribution activity which probably accelerates each time the DJI index forms a peak. Eventually this process leads to a sell-off. It occurred at point C1 in Figure 3, which corresponds to point C1 in Figure 1 and point C in Figure 2. At this point C, the H-function cuts from above to below the RPA line and it results in a non negligible correction, forming a trough just

Figure 3
DJI-ROC and critical values of the RPA for the period June 30, 2009 to November 20, 2009



before point D1 in Figure 1. However, the market reacts to this correction; the H-function cuts again from below to above the RPA line and soon after, a new up trending move is put in place. This intersection occurs at point D, in Figure 2, which corresponds to point D1 in Figure 1 and Figure 3.

Comments

The above empirical results appear to fully support the theoretical findings of the model presented in this paper. At the same time, our analysis demonstrates vividly how the interplay of the RPA and the H- function determines the ROC and gives an insight into how the absolute level of this indicator relates to its mathematical boundaries, set by the prevailing RPA, and feedbacks into the market to shape its direction.

In addition, it is certain that the prevailing value of the RPA, at each moment of the price activity in every market, is what determines whether the ROC is reaching a turning point or not. Inevitably, since the RPA sets the upper and lower limit of the ROC (whatever the case may be), the closer the value of the ROC is to the prevailing value of the RPA, the higher will be the probability that the ROC curve is going to form a turning point. The concept of overbought/oversold conditions is totally relativistic. However, the RPA is a powerful tool in the hands of the technical analyst because, as shown above, it may provide crucial information necessary for assessing objectively the state of the market.

Some implications for technical analysis and trading: The case of overbought/oversold conditions

The traditional RSI (i.e. the calculation of the index on the basis of the well known arbitrary exponential smoothing) is used amongst other purposes, to identify overbought/oversold conditions. However, analysts[xv] and traders[xvi] have expressed various doubts about the ability of the smoothed RSI to effectively assess overbought/oversold conditions. A typical expression of such doubts states:

...when a market exhibits enough of thrust to achieve an overbought/oversold reading it is often a sign that the market intends to trend further. Perhaps another variation of RSI or the combination of another system or method would yield better results as an overbought/oversold indicator, but I must conclude at this point that the RSI identifies trend better than overbought/oversold conditions[xvii].

Overbought/oversold conditions and the use of the exact RSI, the RPA and the ROC to identify in assessment.

Technical analysis of financial markets, at its current state of development does not provide a complete theory to explain overbought/oversold conditions and how they are generated. Consequently analysts and traders, in attempting to set overbought/oversold zones have to resort to empirically derived definitions. One such definition is provided by Jack D. Schwager and states:

A market is considered overbought when an oscillator rallies to an extremely high level and oversold when an oscillator declines to an unusually low level. An overbought market may have risen too far too fast and an oversold market may have fallen too far too fast[xviii].

From the mathematical point of view a very reasonable way to quantify the extent to which a "market may have risen too far too fast…" is by using a ROC reading. Therefore if the above definition is acceptable (and it should be) then the ROC readings provide a quantitative measure of whether a market is entering overbought/oversold zones. Therefore the best way to understand how the RSI relates to such conditions and indeed understand their formation is by using the mathematical relation among the ROC, the exact RSI and RPA described by expression (3.16). On the other hand, **it is because of this unique relationship that the occasional success of the RSI in assessing overbought/oversold conditions is observed.**

However, the same relationship clearly implies that the RSI alone **cannot systematically** predict such conditions. This occurs because the ROC (which by implication of the above definition may be considered a useful quantifier of possible overbought/oversold conditions) is jointly "determined" by the RSI and RPA. Therefore, if the RSI is to be used for assessing overbought–oversold conditions it should be combined with the ROC and the RPA, on the basis of expression (3.16).

Jack Schwager explains further that "momentum and the ROC indicators in their extreme zones suggest that a market is unlikely to trend much further without a correction or consolidation"[xix]. This should be taken to mean that the first warning of the formation of an overbought/oversold situation is given when the ROC is heading or entering into its extreme zone. However, it is currently generally accepted that "bullish or bearish divergence provide additional clues that the market trend is loosing at least some of its power"[xx]. Therefore from the point of view of technical analysis and the main thesis of this paper, the following points are in order:

(a) From the point of view of technical analysis

To argue that the signal of an overbought/oversold market is provided when the oscillator (say RSI) is falling from an extreme level back into the "normal" area may be contradicting the very meaning of a trading signal (which is required to warn prior to or confirm very early after a reaction about the changing mood of the market). Indeed conceptually, such a movement confirms historically (i.e. ex-post), that a price area acted as an overbought/oversold zone, i.e. the specific area of the extreme level. Hence, it cannot be thought as a technically meaningful signal. Therefore, the fact that the divergences mentioned above **do** "provide additional clues" of an imminent change in market trend, should not necessarily be taken to imply that the relevant signal is the move of the indicator considered, from an extreme level back to the "normal area".

(b) From the point of view of the thesis of this paper.

On the other hand, the fact that "**additional clues**" may be required, in addition to the oscillator heading towards or entering into the overbought/oversold zone, in order to confirm an imminent change in market trend, implicitly admits "a missing variable" from the underlying model. This missing variable is the value of the RPA compared to that of the exact RSI as provided by equation (3.16) and equation (3.17), and which comprise one of the main theories presented in this paper.

An arithmetical example

First: the explanation why the RSI on its own, cannot identify overbought/oversold conditions. Using the model presented in this paper and particularly expression (3.16), we have constructed Table 8.

It is assumed that the starting price for seven different stocks is $4. The net price activity (NPA) as defined by expression (2.19) is taken for all of them at $0.8. Then by assuming various readings for Total Price Activity (TPA), the UP values are calculated by combining expressions (2.34) and (2.19), as follows:

$$\mathrm{UP} = \frac{TPA + NPA}{2}$$

So for the stock in Case Number (1), the relevant UP value is $0.9, arrived at on the basis of the above expression and assuming as shown in Table 8 that TPA is $1, as follows:

$$\mathrm{UP}\ \ (\text{case } 1) = \frac{\$0.8 + \$1.00}{2} = \frac{\$1.8}{2} = \$0.9$$

The RSI is obviously obtained by dividing the above result by the relevant TPA (i.e. $1) to yield a reading of 0.9 (or 90%).

Table 8

Various RSI and RPA readings compatible with the unique relation between them and a ROC reading derived from a specific net price activity and starting price.

CASE	STARTING PRICE	NPA	DERIVED ROC	TPA	UPS	RSI	2RSI-1	RPA	ROC
1	4	0.8	0.20	1	0.9	0.9000	0.8000	0.250	0.200
2	4	0.8	0.20	1.4	1.1	0.7857	0.5714	0.350	0.200
3	4	0.8	0.20	1.5	1.15	0.7667	0.5333	0.375	0.200
4	4	0.8	0.20	2	1.4	0.7000	0.4000	0.500	0.200
5	4	0.8	0.20	2.1	1.45	0.6905	0.3810	0.525	0.200
6	4	0.8	0.20	2	1.4	0.7000	0.4000	0.500	0.200
7	4	0.8	0.20	3	1.9	0.6333	0.2667	0.750	0.200

The RPA, by definition is arrived at by dividing the TPA by the starting price. Therefore, for Case Number (1) it is \$0.25 (i.e. 1/4 = 0.25). With \$4 as a starting price and NPA generated over the period considered at 0.8, the closing price at the end of the period is \$4.8, because of expression (2.19). The term "derived ROC" in Table 8 means the reading for the ROC derived from its very definition, i.e. on the basis of expression (2.21). On the other hand, the ROC in the same Table is the ROC reading obtained by multiplying the H -function by RPA, on the basis of expression (3.16). These two readings are always identical except when the exponentially smoothed RSI is used instead of the exact RSI.

Thus, Table 8 presents a set of circumstances where there are various readings for the RSI and RPA, with all of them yielding the same ROC. The readings for the RSI vary from 0.6333 to 0.90. **The question is obvious: Which reading (or readings) of those presented in Table 8 do actually reveal an overbought condition? Following accepted practices one should be prepared to close trades where the RSI reached above 0.70. Is this appropriate?**

For the cases presented in Table 8 the answer is "yes", only for Case Number (1). This is not only because the RSI is 0.90 but the following facts are considered as well:

a. The ROC is already very close to its upper limit which is the corresponding value of the RPA. Indeed, the ROC is only 20% below its maximum possible value under prevailing conditions.

b. The RSI is only 10% away from its highest positive value (+1). Even for purely mathematical reasons a reversal may be imminent. Such a reversal (due, to say, a small reduction in price) could cause (because of the very high current level of RSI) a rather sharp decline in (2RSI -1) which will either bring the H- function very close to the RPA or force a cut of the RPA line from above to below by the H- function. For the reasons explained when the properties of the RPA were discussed, most probably, such a development would render the ROC equal to $(RPA)^2$, i.e. $(0.25)^2 = 0.0625$, which is well below the current reading of the ROC. Such an event could easily lead to a sell-off with a further reduction in the closing prices and the ROC.

The above points do not hold true for Cases Number (2) and (3) in Table 8. Therefore it cannot be concluded with certainty that because the RSI is well above 0.70 the stocks considered are within an overbought zone or are entering into it.

On the other hand, Cases Number (4) to (6) are characterised by an RSI at close to or at 0.70. **Should trades on these stocks be closed on grounds that they are entering an overbought zone?** Any rational answer to this question and the implied trading decision should consider the following facts:

- In all of these cases the RPA is above or equal to 0.50 i.e. 50% below its upper boundary and therefore has enough margin to move upwards.
- The ROC at 0.20 for all these cases, is about 60% below its maximum possible value which is the current RPA.
- The reading for (2RSI-1) is not very high and it is below the RPA. This implies that a further up move could force the RSI functions to cut from below to above the RPA line. This would render the ROC equal to $(RPA)^2$ i.e. just about 0.25, well above the current reading.

Final comments

The purpose here was not to construct a new trading system but to point out certain logical consequences of the model presented and especially of the mathematical relationship among the ROC, the RSI and the RPA. It is true however that these consequences provide theoretical support to the empirical doubts about the ability of the RSI to identify overbought/oversold conditions, as previously stated. Under certain circumstances they may also provide a theoretical basis justifying the "RSI is wrong" theory. This theory expressed in trading terms requires "…rather than looking for a top when the overbought level is penetrated, buy the issue and use a sell stop"[xxi].

Conclusions

This paper exploits the analytical power of the original RSI concept by deriving its logical implications on the basis of a simple mathematical model. The first implication is the measure of the exact-RSI. This reflects the true meaning of the original RSI concept. It is shown to be independent of the so called RS ratio. The second implication is the derivation of a unique relation that exists between the exact RSI and the ROC oscillator. This is established by making use of the Relative Price Activity (RPA©) index, within the analytical framework of the mathematical model employed for the purposes of this paper. The RPA index measures total price activity (i.e. the sum of the absolute values of all price changes that occurred within the time period considered which are necessary to calculate the RSI), relative to the level of the closing price at the beginning of this period, which is taken as the reference price.

The findings of this paper are that in every moment of price activity, the ROC is a fraction of the RPA. The sign and size of this fraction is determined by a linear function of the exact-RSI, referred to as the H-function of RSI. This rule for the RPA sets the natural boundaries for the ROC, (i.e., its upper and lower limits) and the size of its absolute value. This holds true in all markets and in every moment of price activity. However, this is distorted if the well known (and currently in global use), exponentially smoothed RSI is adopted, instead of the exact-RSI.

Furthermore, it is argued that when the current value of the ROC is compared with certain critical levels of the RPA, along with the prevailing value of the exact-RSI, it yields information that may improve our technical understanding of the state of a market. In addition, such an exercise could provide an insight as to the possible direction of the market in the immediate future.

The findings further explain that the RSI, on its own, is not able to successfully identify overbought/oversold zones in a systematical way. This is a direct logical consequence of the rule relating the ROC to the RSI and the RPA. On the provision that the ROC oscillator may be considered as a reasonably acceptable instrument to signal that the market is entering or has entered an overbought/oversold zone. Hence, it is argued that the appropriate way to identify overbought/oversold states of the market, is by using jointly the RPA and the H-function, as determined by the prevailing reading of the exact RSI. Relevant investigation, for this purpose, should be conducted on the basis of the mathematical rule relating the ROC to the RSI and RPA. The ROC oscillator would signal that the market is entering an overbought/oversold zone once its value reaches certain benchmarks. These benchmarks, to be meaningful must be set in relation to the value of the RPA which determines the natural boundaries for the ROC. However, the RPA is a result of market activity and therefore it varies over time following alterations in the state of this activity. It is for this reason that the paper points out the relativistic character of the overbought/oversold concept. Indeed, an overbought/oversold situation is a clear relativistic phenomenon. When in place, it is the power of this relativistic phenomenon that will determine the reaction of the market and the strength of this reaction i.e. whether the reaction is a temporary correction, a sharp correction and a drastic reversal.

When necessary, the discussion related some of its theoretical findings of the analysis presented to various empirical reservations in the literature on the RSI, regarding the ability of the RSI to identify overbought/oversold zones. **IFTA**

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Book Reviews

Trading Regime Analysis – The probability of volatility

by Murray Gunn – reviewed by Regina Meani

Murray Gunn presents a candid and insightful journey through technical analysis and various trading regimes, drawing on his more than 20 years experience in the markets.

He offers a valuable contribution to the Technical Analysis body of Knowledge with the introduction of two new indicators: the Trend-Following Performance Indicator (TFPI) and the Trading Regime Indicator (TRI).

Murray begins the journey on a controversial note claiming there is NO holy grail and advises readers that 'I have come to the not so startling conclusion. *Everything works…some of the time*'[i]. This provides Murray's very pragmatic theme which he carries through the book which at times takes on a quite jovial tone. One of his quotes in chapter two 'never make predictions, especially about the future'[ii] which he attributes to either of two baseball legends, Casey Stengel or Yogi Berra, is a humorous quote as he suggests, with blinding wisdom.

In Chapter three, he takes on the task of explaining volatility, a concept understood by few and demystifies it with: 'Volatility is not only referring to something that fluctuates sharply up and down but is also referring to something that moves sharply in a sustained direction'[iii] With this he has set the stage for his *Trading Regime Analysis* but first he moves to Part II where he takes us through some of the essentials of technical analysis from orthodox pattern recognition to Donchian Channels with a final "nod to the quants". Here he presents an interesting juxtaposition and delivers an entire chapter on quantitative analysis, something not often seen in the world of TA.

As he delves into the problem of determining how and when one should shift a trading strategy i.e when the market changes from either trending or ranging, he acknowledges the contribution by quantitative research but remains loyal to his TA background arguing that technical analysis has the better tools to identify these changes ahead of a change in the market's direction.

In Part III Murray's proposes his identifying tools: Using the tolerances for the differences between moving averages and then introduces his Trend-Following performance Indicator (TFPI) and moves on to his Trading Regime Indicator (TRI) which combines standard deviation with moving average analysis. The author claims that his indicators are not prefect but that they can give a very good idea of the probabilities of the likely trading environment.

Part IV brings it all together as he outlines the usefulness for his trading regime analysis for traders and investors in the application of short and longer-term strategies.

Trading Regime Analysis presents a down to earth approach, striking a cord as he reminds us that there is no holy grail and that no one trading strategy works all the time. Tackling the difficult problem of when to know a market is changing Murray Gunn has provided us with some workable ideas.

The review copy was provided courtesy of The Educated Investor Book Shop, Melbourne Australia (see advertisement page 71) **IFTA**

'I have come to the not so startling conclusion. Everything works… some of the time'.

Murray Gunn

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Book Reviews

Cloud Charts – Trading Success with the Ichimoku Technique

by David Linton – reviewed by Larry Lovrencic

So, what is Ichimoku? The full name of the method is Ichimoku Kinko Hyo which means 'at one glance balance bar chart'.

Larry Lovrencic

My introduction to Ichimoku charts was at the 1997 IFTA conference held in Sydney. During a conversation with Dan Gramza, from Chicago, who teaches the Japanese Candlestick method, and members of the Japanese contingent, Dan steered the discussion to Ichimoku. I thought to myself *'What was that? Itchy what? Ah, Ichimoku, that Japanese method steeped in mystique'*. Our Japanese colleagues did their best to explain but found it very difficult to do so in a quick informal chat. Intrigued by the encounter, I went off searching for anything I could find about Ichimoku, with little immediate success. Over the years, there have been only a few works which have made their way to English translation and a few written by Western converts.

David Linton, the author of *Cloud Charts*, had his interest in Ichimoku charts 'sparked' during a presentation by Rick Bensignor at the 2004 IFTA conference in Madrid. David had heard of the method prior to the conference but credits Rick with presenting it in an 'understable' way. David set out on a quest for Ichimoku knowledge. He researched the internet, questioned Japanese delegates at subsequent IFTA conferences, sought out Rick Bensignor at conferences and meetings and even flew to Tokyo. The fruit of that quest is the book, *Cloud Charts*.

The Ichimoku method is now fast becoming popular in Western trading rooms and is available on almost all technical analysis software. David must take some credit for turning what seemed to be an exotic and complicated method into an easily understandable and robust trading and analysis tool for non-Japanese speaking technical analysts.

So, what is Ichimoku? The full name of the method is Ichimoku Kinko Hyo which means 'at one glance balance bar chart'. Ichimoku charts were devised by Goichi Hosoda, a Tokyo journalist, who believed that once the method was fully understood, one could comprehend the exact state of a market at a glance. Most of the Ichimoku indicators represent equilibrium in one time frame or another and price action is generally analysed with regard to whether the market is in equilibrium, moving away from it or reverting back to it. By their nature, the various indicators also offer dynamic areas of support or resistance.

Cloud Charts is divided into three parts. The first is for the novice technical analyst and is designed to give them an understanding of many basic technical analysis concepts involved with not only Ichimoku analysis but also traditional techniques. More experienced technical analysts may wish to skip this part.

Part two introduces the reader to the basic indicators used in Ichimoku charts (David calls them cloud charts). This section deals with the derivation and interpretation of:

1. **The Turning Line** (also called the Conversion Line)
2. **The Standard Line** (also called the Base Line)
3. **The Cloud Span A** (also called the Cloud Span 1)
4. **The Cloud Span B** (also called the Cloud Span 2)
5. **The Lagging Line** (also called the Lagging Span)

Part two offers a guide to applying Ichimoku charts in a multiple time frame sense, as well as the often overlooked Wave Principle, Price Targets and Time Span Principle. However, the application of Ichimoku charts to price and time projection is very subjective and for that reason alone the projections are quite often not utilised by even experienced analysts.

Looking at an Ichimoku chart, it's no surprise that analysts are sometimes turned off by the busyness of the chart. It can look like chaos to the uninitiated but the key to getting past that is understanding the formula to each indicator, how they combine with each other, how they represent a consensus of price action in different time frames and colour-coding. In part two David explains construction and interpretation of the charts in a manner that is easy for any newcomer to technical analysis let alone a professional on a trading desk.

Part three, my favourite part of the book, is where we are encouraged to think outside of the box. Here, the use of Ichimoku charts are combined with other technical analysis techniques, alternative time inputs into the indicators are suggested and the application to market breadth analysis is considered. There is also a chapter on back testing for the quantitative traders to consume.

Overall, this book, in an easily read manner, brings together the body of knowledge of a Japanese technical analysis method which was once thought of as exotic and over-complicated. It has potential to become the definitive English language text on the Ichimoku Kinko Hyo technical analysis method.

The review copy was provided courtesy of the author and Updata Plc , United Kingdom.(see advertisement page 4) **IFTA**

Part three, my favourite part of the book, is where we are encouraged to think outside of the box.

Larry Lovrencic

Author Profiles

The theory of the Relative Strength Index (RSI)...is probably one of the most important breakthroughs in the effort to quantify traditional bar-reading techniques of classical trend analysis. Its purpose is to make the visual readings of chart trend analysis more objectively understood, by "summarizing" price activity shown on bar-charts in terms of uniquely determined numbers.

Ioannou p.54

The most important aspect with Cloud Charts is how the price interacts with the cloud. Because the cloud is constructed purely from price action, price movement creates its own boundaries of resistance and support with the cloud into the future... Price action interacts with the cloud running ahead of itself on a perpetual basis providing a unique roadmap for future price behaviour.

Linton p.12

Periods of acute and unprecedented turbulence in markets enhance researchers' threshold for seeking alternative explanations – explanations that run contrary to inferences based on well-established Gaussian models. Such excursions into uncharted territories reflect not only the evolving realisation of the complexity of the financial markets, but are also an acknowledgement of the limitations of Gaussian models – models whose underlying mathematical and statistical assumptions fail to truly reflect real-world characteristics of asset prices.

Mandhavan & Pruden p.37

Joshua Dayanim

Joshua Dayanim is the founder of Market Dynamix, a website dedicated to providing investor information and education on Market Dynamics. As an independent investor, he has studied various approaches to security pricing and personal investment management. This eventually led to the development of Market Dynamics, providing a model for security pricing movements and formation of support and resistance levels. He holds Masters degrees in Business Administration and Electrical Engineering, with an undergraduate focus in Physics.

Julius de Kempenaer

A Director of Taler Investment Consulting in Amsterdam Julius' prior positions include: Head of Technical Analysis at Kempen & Co. in Amsterdam, Head of Technical Analysis at Amstgeld Effectenbank, Amsterdam and Rabobank International, Utrecht. He began his career in the financial markets in 1990 as Portfolio Manager at Equity & Life Insurance in The Hague, after having served several years in the Dutch Air Force.

Julius holds a post graduate qualification in Portfolio Construction and Asset Allocation from the FREE University of the Netherlands and a degree in Economics from the Dutch Royal Military Academy. He is Chairman of the Dutch Commission of Technical Analysis (DCTA) and is a director for IFTA.

Pavlos Th. Ioannou

A full-time technical trader since 2005, Pavlos accepts occasional training and consultancy assignments. He holds a Bachelor of Science (Econ), a Master of Science (Econ; LSE), and the MFTA (2010 John Brooks Memorial Award) and is a member of the Australian Technical Analysts Association (ATAA). He is a Chartered Member of the Institute of Logistics and Transport (UK) and in 1993 earned a Fulbright Scholarship (CASP), for short duration studies in the USA.

In 1986, he joined the international consulting community and worked as an Infrastructure Economist and Project Manager/Director, for various I.B.R.D. and IDA projects in Ethiopia, Ghana, Cyprus, Mexico and Indonesia, specialising in the economic and financial appraisal of transport related projects. Currently his main research interest is the microeconomic foundation of key concepts of technical analysis and the application of mathematical and quantitative methods to exploit the full potential of these concepts.

David Linton

David received an engineering degree at King's College, University of London, after which he began dealing in Traded Options on the London Stock Exchange and developed computer software for analysing price behaviour. In 1991, David founded Updata plc, based in London, where he is Chief Executive Officer.

A well known commentator in the financial media, David has taught technical analysis over the last two decades with numerous financial institutions employing him to teach and train their trading teams. He is a member of the UK Society of Technical Analysis (STA) where he teaches the Ichimoku technique as part of the STA Diploma Course and is a member of the Association of American Professional Technical Analysts (AAPTA). He was awarded the Master of Financial Technical Analyst (MFTA) for his paper on the Optimisation of Trailing Stop-losses in 2008.

Larry Lovrencic

A foundation member and Vice President of the Australian Professional Technical Analysts (APTA), Larry is a Life Member, a member of the Board of Directors and a former National Vice President of the Australian Technical Analysts Association (ATAA).

He is a Senior Fellow of the Financial Services Institute of Australasia (FINSIA), holds the Graduate Diploma in Applied Finance and Investment, lectures and chairs the Task Force for the Fin231 Technical Analysis subject offered by Kaplan Higher Education (Australia), chaired the Advisory Committee for the E171 Specialised Techniques in Technical Analysis subject and regularly presents Technical Analysis seminars to members of the financial services industry in South East Asia. Larry was awarded the Diploma in Technical Analysis (Dip. TA) by the ATAA and holds the Certified Financial Technician (CFTe) designation. Larry Lovrencic is the principle of IchimokuCharts.com

Vinodh Madhavan

Vinodh's research interests include exploring non-linear time series analysis, long-term dependence, CDS indices, and contagions. He recently completed his Doctor of Business Administration program at Golden Gate University, San Francisco and has been awarded the "2009-2010 Outstanding Graduate Student – Doctor of Business Administration" Award by the Dean of Ageno School of Business. He also holds a Bachelors degree in Electrical and Electronics Engineering and a Postgraduate degree in Manufacturing and Operations Management. He currently serves as an Adjunct Faculty at Golden Gate University. In addition, he holds the "Malcolm S.M. Watts III Research Fellowship" position at Technical Securities Analysts Association of San Francisco (TSAAF). Vinodh is currently working on a paper aimed at interpreting non-linear behaviour of his dissertation data sets, by employing methodologies found in the field of chaos theory.

Regina Meani

Regina covered world markets, as technical analyst and Associate Director for Deutsche Bank before freelancing. She is an author and has presented internationally and locally and lectured for the Financial Services Institute of Australasia (FINSIA), Sydney University and the Australian Stock Exchange. She is President of the Australian Professional Technical Analysts (APTA) and Journal Director for IFTA. Regina carries the CFTe designation. She has regular columns in the financial press and appears in other media forums. Her freelance work includes market analysis, private tutoring and larger seminars, training investors and traders in Market Psychology, CFD and share trading and technical analysis. Regina is also a director of the Australian Technical Analysts Association (ATAA) and has belonged to the Society of Technical Analysts, UK (STA) for over twenty years.

Prof. Henry (Hank) Pruden

An acclaimed author of books and dozens of articles on behavioural finance, trader psychology, and technical analysis, Hank is Professor of Business Administration and the Executive Director of the Institute for Technical Market Analysis at Golden Gate University, San Francisco. He is the president of the Technical Securities Analysts Association of San Francisco (TSAASF) and has served on the board for the Market Technicians Association (MTA) and for IFTA. Hank is a member of the American Association of Professional Technical Analysts, USA (AAPTA). In the past decade he has been a speaker on every continent except Antarctica. Distinguished by several universities with prestigious awards, He has also been honored for excellence in education by the MTA and for Outstanding International Achievements in Behavioral Finance and Technical Analysis Education by P.I. Graduate Studies of Kuala Lumpur, Malaysia. In 2006, his research was highly commended by the Emerald Literati Network Awards for Excellence.

Zurab Silagadze

Zurab Silagadze graduated Tbilisi State University, Georgia in 1979. In 1986 he moved to Novosibirsk where he gained his PhD in theoretical and mathematical physics in 1995. Zurab currently is a senior researcher at Budker Institute of Nuclear Physics and is assistant professor at Novosibirsk State University.

Ralph Vince

Ralph Vince has worked as a programmer for numerous private investors, fund managers, professional gamblers and private trusts and has held the Derivatives/Forex Chair for the Market Technicians Association (MTA) in the USA. In the late 1980s Ralph began to detail his Optimal *f* notion for geometric mean maximization and application in the financial markets, and provided a scope and level of detail to geometric mean maximization and the consequences involved in its ignorance, which lends a framework and rigor to money management. In quantifying drawdown along with geometric mean maximization, his work has developed into the Leverage Space Portfolio Model and he has utilized this framework to attempt to maximize the probability of profitability.

Rolf Wetzer

Rolf heads the Bonds and Rule Controlled Investment departments at Bank Sarasin's institutional asset management in Basel, Switzerland. Prior to this, he was a Senior Fund Manager for foreign exchange and interest rate funds at MunichRe Asset Management in Munich and before this Rolf worked at Dresdner Asset Management as a Portfolio Manager for both balanced and fixed income portfolios.

Gaining a PhD in econometrics from the Technical University of Berlin and graduate degrees in Business Administration from both the Technical University of Berlin and the Toulouse Business School in France, Rolf now lectures at both institutions in Quantitative Trading Strategies. In 2006 he was awarded the "Best German Technical Analyst" by the VTAD (German Society of Technical Analysts) and was runner up in 2007. Rolf is a member of the Swiss Association of Market Technicians (SAMT) and the German Statistical Society.

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