IFTA Journal | 2016 Edition

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IFTA Journal

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Whatever the mind of man can conceive and believe, it can achieve

—Napoleon Hill

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About cover photo:
Seascape in peaceful day
—Painting by Ilbusca

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IFTA Certified Financial Technician

Certified Financial Technician (CFTe) Program

IFTA Certified Financial Technician (CFTe) consists of the CFTe I and CFTe II examinations. Successful completion of both examinations culminates in the award of the CFTe, an internationally recognised professional qualification in technical analysis.

Examinations

The **CFTe I** exam is multiple-choice, covering a wide range of technical knowledge and understanding of the principals of technical analysis; it is offered in English, French, German, Italian, Spanish and Arabic; it's available, year-round, at testing centers throughout the world, from IFTA's computer-based testing provider, Pearson VUE.

The **CFTe II** exam incorporates a number of questions that require essay-based, analysis responses. The candidate needs to demonstrate a depth of knowledge and experience in applying various methods of technical analysis. The candidate is provided with current charts covering one specific market (often an equity) to be analysed, as though for a Fund Manager.

The CFTe II is also offered in English, French, German, Italian, Spanish and Arabic, typically in April and October of each year.

Curriculum

The CFTe II program is designed for self-study, however, IFTA will also be happy to assist in finding qualified trainers. Local societies may offer preparatory courses to assist potential candidates. Syllabuses, Study Guides and registration are all available on the IFTA website at http://www.ifta.org/certifications/registration/.

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CFTe I $500 US	CFTe I $700 US
CFTe II $800* US	CFTe II $1,000* US

*Additional Fees (CFTe II only):
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Your paper must meet the following criteria:

- It must be original
- It must develop a reasoned and logical argument and lead to a sound conclusion, supported by the tests, studies and analysis contained in the paper
- The subject matter should be of practical application
- It should add to the body of knowledge in the discipline of international technical analysis

Timelines & Schedules

There are two MFTA sessions per year, with the following deadlines:

Session 1	
"Alternative Path" application deadline	February 28
Application, outline and fees deadline	May 2
Paper submission deadline	October 15

Session 2	
"Alternative Path" application deadline	July 31
Application, outline and fees deadline	October 2
Paper submission deadline	March 15 (of the following year)

To Register

Please visit our website at http://www.ifta.org/certifications/master-of-financial-technical-analysis-mfta-program/ for further details and to register.

Cost

$900 US (IFTA Member Colleagues);
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International Federation of Technical Analysts

Letter From the Editor

By Aurélia Gerber, MBA, CFA

Dear IFTA Colleagues and Friends:

This year's 28th Annual Conference in Tokyo is under the theme *Continuous Progression in Investment Management and Omotenashi in Technical Analysis.* It is always exciting to travel, taste the local flavour, and discover a new culture. This is also the time for market technicians from around the world to gather, speak the same language, and share their interesting ideas.

The *IFTA Journal*—through its global distribution to industry professionals from member societies comprising 27 countries—is one of the most important forums to publish leading work in technical analysis.

The art of mixing modernity and tradition, very much seen in the Japanese culture, is what we strive to achieve in this year's *IFTA Journal.* Some very old techniques are being revisited, and some newer techniques are evoked, both bringing us a little further on the knowledge journey. The principles of technical analysis remain the same, however: price discounts everything; price movements are not totally random—they move in trends; and history has a tendency to repeat itself.

Continuous Progression in Investment Management and Omotenashi in Technical Analysis

This year's *Journal* is divided in four sections. The first section includes articles submitted by IFTA colleagues. Two came from the Vereinigung Technischer Analysten Deutschlands (VTAD) and discuss a scientific approach to Fibonnacci retracements and the application of a newer technique to the well-known candlesticks charts dating back to the 18th century, which will be of interest to system developers. One article was submitted by the Society of Technical Analysts (STA) on the analysis of the profitability of trading signals generated using Ichimoku cloud charts.

In the second section, we have published four Master of Financial Technical Analysis (MFTA) research submissions. This body of work offers fresh ways of looking at the behavior of markets and is testament to the high standing of the MFTA designation. Two articles deal with the introduction of new indicators—one based on the relationship between Web searches and trading volumes using advanced statistical techniques and one on being able to measure the acceleration/deceleration of relative strength with satisfactory market timing results. Another paper studies entry technique using various historical volatility filters in conjunction with a high probability mean reversal trading system. Finally, we learn about market anomalies left as clues by dividend investors making an investment strategy profitable.

Next, with the permission of the National Association of Active Investment Managers (NAAIM), we are happy to include a paper by Charles Bilello and Michael Gayed, winner of the NAAIM Wagner Award 2014. We hope that you find this paper interesting.

We are also very thankful to have had the support of our book proposal reviewer, Regina Meani, on *Technical Analysis of Stock Trends –Tenth Edition,* by Robert D Edwards, John Magee, and W.H.C. Bassetti.

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

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

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

Fibonaccis Are Human (made)

By René Kempen

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Abstract

In this article, a scientific approach to retracements is introduced and the myth of Fibonacci retracements refuted. The statistical analysis of the retracement data resulting from the application of the MinMax-process by Maier-Paape to a variety of stock markets reveals a logarithmic normal distribution of the retracement values in general. It is deduced that there are no overall statistically significant retracement levels. While in a local environment the 100% retracement do show significance, the Fibonacci retracements are not seen empirically.

Introduction

In the field of technical analysis today's trader can choose between a myriad of different indicators, filters, and even whole trading systems. On the one hand, this shows the creativity of the technical analysis community. On the other hand, however, the variety of tools indicates the complexity of chart analysis. The market's behavior obviously cannot be predicted by a set of analysis tools.

Consider a specific chart tool—whether it is a simple line, an indicator, or a trading system—that is to be applied to a specific market. In this case, the question arises as to whether or not the combination of tool and market works as intended. A certain answer to this question cannot be given, since it would require detailed knowledge of the market's progression in the future. As long as this information is not available, any testing has to be based on historical market data.

Trading systems are commonly empirically tested by applying a backtest. However, trading systems are usually a combination of other tools, such as indicators. Thus, testing the system as a whole is insufficient to derive statements for each individual component. In fact, it is possible to have defect components even though the backtest succeeded. A more basic approach, therefore, would be to empirically test each component individually. However, this approach is rarely seen, and fundamental books within the field of technical analysis miss it completely (see Murphy, 2008). Instead, statements are commonly based on a few examples only. Such an inductive approach, however, cannot hold when considering scientific aspects, which would in fact require a deductive approach. Conclusively, a concept has to be systematically tested considering a variety of examples before any knowledge can be deduced from the set of results. Indeed, this article aims at testing the concept of Fibonacci retracements using such a deductive approach.

Fibonacci ratios

The Fibonacci numbers 1, 1, 2, 3, 5, 8, 13, ... are one of the best known series and are even present in diverse areas of nature. The n-th Fibonacci number is built of the sum of the two previous numbers, or in mathematical terms, the n-th Fibonacci number denoted by fn is defined as

$$f_n = f_{n-1} + f_{n-2} \quad \text{for } n > 2 \qquad (1)$$
$$\text{with } f_2 = f_1 = 1.$$

Since the appearance of the Elliott-Wave-Theory (R.N. Elliott, 1920, see Frost and Prechter, 2005), technical analysts have been well acquainted with Fibonacci. Furthermore, already Johannes Kepler had been interested in the ratio of two consecutive Fibonacci numbers f_{n+1}/f_n. He found that this ratio approaches the value of the golden ratio Φ for large n:

$$lim_{n\to\infty}\frac{f_{n+1}}{f_n} = \Phi = \frac{1+\sqrt{5}}{2} \approx 1.618\ldots.$$

Generally, the k-th Fibonacci ratio F_k is given by the limit of the ratio of a Fibonacci number with its k-th successor meaning the following in mathematical terms:

$$F_k = \lim_{n\to\infty}\frac{f_n}{f_{n+k}} = \lim_{n\to\infty}\underbrace{\frac{f_n}{f_{n+1}}}_{\to\Phi^{-1}}\underbrace{\frac{f_{n+1}}{f_{n+2}}}_{\to\Phi^{-1}}\cdots\underbrace{\frac{f_{n+k-1}}{f_{n+k}}}_{\to\Phi^{-1}} = \Phi^{-k} = \left(\frac{1+\sqrt{5}}{2}\right)^{-k}. \qquad (2)$$

With this formula, the first Fibonacci ratios can be calculated:

$$\begin{aligned} F_0 &= \left(\frac{1+\sqrt{5}}{2}\right)^0 = 1 \\ F_1 &= \left(\frac{1+\sqrt{5}}{2}\right)^{-1} \approx 0.618034\ldots \\ F_2 &= \left(\frac{1+\sqrt{5}}{2}\right)^{-2} \approx 0.381966\ldots \end{aligned}$$

Fibonacci retracements

The Fibonacci ratios are applied in the analysis of trends. While the basic concept of a trend has been fundamental in the field of technical analysis since Charles H. Dow introduced it, the specific characterization of a trend is not unique. In this article, the market-technical definition of a trend is used.

1. Definition (market-technical trend)

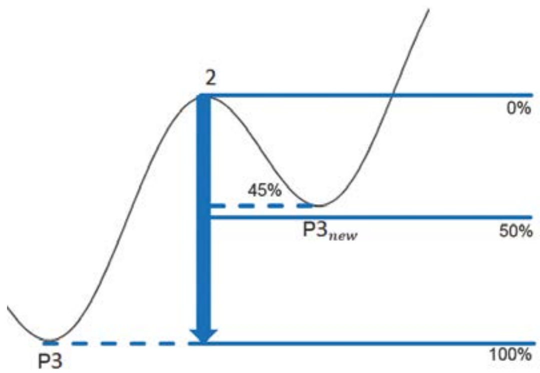
A market is in an *up/down-trend* if and only if (at least) the two last relevant *lows* (denoted by P1 and P3) and *highs* (denoted by P2) are monotonically increasing/decreasing. Otherwise, the market is currently *trendless*. In case of an uptrend, the phase between a low and the next high is called the *movement*. In the same manner, the phase between a high and the next low is called the *rectracement*. In case of a downtrend, movement and retracement are defined in the exact opposite way.

In line with the notation used for defining a trend, it is practical to number the highs and lows in 1-2-3 manner (see Voigt, 2013).

Now, the correction is the part where Fibonacci ratios occur. In particular, it is common to indicate the amount of correction denoted by the retracement value R in unities of the preceding movement. That is, for any trend with last three extrema $P3_{\mathrm{new}}$, $P2$ and $P3$ (see Figure 1) the retracement value R is given by

$$R = \frac{P2 - P3_{\mathrm{new}}}{P2 - P3}. \qquad (3)$$

Figure 1. Retracement level within a trend.



In the field of technical analysis, particular retracement values usually occur as support- and resistance-level but sometimes also as predictions for the next actual retracement. Indeed, the trend is obviously broken if $R > 100\%$. Assuming that a trend is more likely to continue than to break, the 100% retracement then is commonly considered as support level (see Murphy, 1999, chap. "Support and Resistance"). On the other hand, based on Dow, the retracement levels 33%, 50% and 67% are taken as predictions for the correction. Besides these, the mentioned Fibonacci retracements are the retracement levels with the values of the first Fibonacci ratios. In particular, the first two Fibonacci ratios $F_1 \approx 0.618032$ and $F_2 \approx 0.381966$ are of special interest. However, the usefulness of any specific retracement value (that includes Fibonacci retracements) as prediction has not scientifically been examined yet. To be able to do so, the retracement values have to be automatically captured.

MinMax process

Based on the trend definition (1), an automatic detection of relevant highs and lows is needed. Such an algorithm has been accomplished by Maier-Paape (2015). He defines a *MinMax-process* based on any SAR-process (stop and reverse) by searching for relevant highs when the SAR-process indicates an up movement and searching for relevant lows when the SAR-process indicates a down movement. By choosing a specific SAR-process one can affect the sensitivity of the detection (e.g., to match different trend classes, see Murphy, 1999, chap. "Dow Theory"), while the actual detection algorithm works objectively without the need of any other parameter. In the measurement, this MinMax-process with underlying integrated MACD direction-process with one scaling parameter (see Maier-Paape, 2015, chapter 2.1) is used. While the MACD process usually needs three parameters (fast-, slow- and signal-line), the integrated MACD process used here only needs one single scaling parameter due to the fact that it fixes the ratios between the different lines and then scales all three parameters at once (i.e., fast: 12 scaling, slow: 26 scaling, signal: 9 scaling). The utility of this setting is visualized by the following example:

Retracement measurement

The previously introduced MinMax-process based on the integrated MACD SAR- process with scalings 0.5, 1 and 4 is applied on each stock of the current Dow30, Nasdaq100 and Dax30. For each stock the daily chart with a maximal period covering from January 4, 1974 to January 30, 2015 is taken. From the resulting list of highs and lows, the retracement values and the wavelengths (distance of time between two highs or lows) of the trends are captured with no distinction between up- and down- trends (the wavelengths will be used to assign three different scaling parameters to the three different trend classes). It should be noted that the scaling parameter of the direction process directly affects the sensitivity of the MinMax-process (see Fig. 2) in a way that lower scalings lead to more data but at the

Figure 2. Daily chart of Deutsche Boerse with MinMax indicator based on the integrated MACD SAR-process with different scalings (green: 0.5, blue: 1, black: 4), which control the sensitivity of the MinMax-process. Each line indicates the last corresponding extreme value.

same time to shorter wavelengths. In doing so, the focus of the examination can indirectly be put on a specific trend class (primary, secondary or tertiary according to Dow). The scalings, therefore, are deliberately chosen with the aim of respecting all three trend classes. The retracement measurement in this configuration led to the following amounts of data: primary trend (scaling 4) a total of 4.915 values, secondary trend (scaling 1) a total of 17.931 values and tertiary trend (scaling 0, 5) a total of 35.684 values.

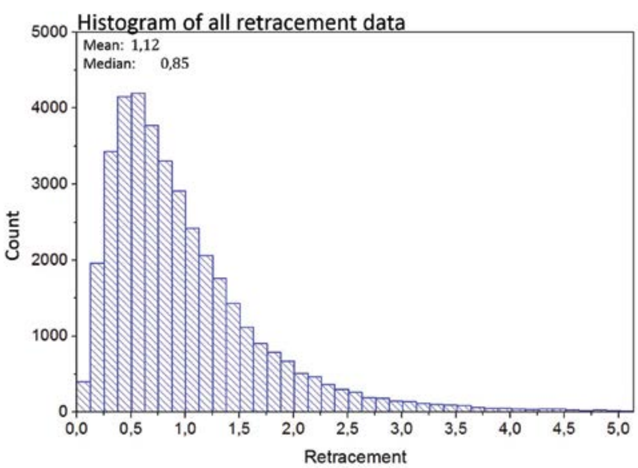
Analysis, first insights

To verify the partition of the data into three trend classes, which has already been done, the evaluation of the wavelength is first.

- Scaling 4 (primary trend): mean 117, median 107 days.
- Scaling 1 (secondary trend): mean 33, median 30 days.
- Scaling 0, 5 (tertiary trend): mean 17, median 15 days.

Based on the collected retracement data, three histograms then are filled: one for each trend class or scaling parameter, respectively. The histogram of all 17.931 retracement values corresponding to the secondary trend reveals the following distribution:

Figure 3. Histogram of retracement data for scaling 1 in the range of 0 to 5 with a total of 42 bins and a bin size of 0, 12.



When analyzing and evaluating the data, the term "statistical significance" occurs frequently. This means the following in general:

2. Definition

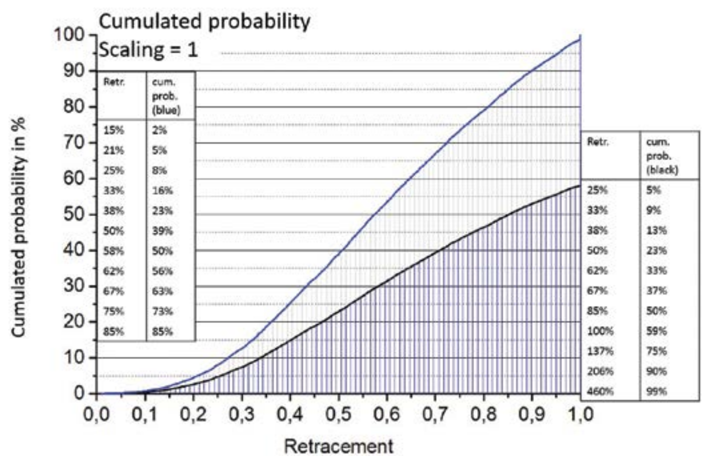
May a value differ from a given model. Then, this value is called statistically significant if the probability that the deviation from the model occurred accidentally is smaller than a certain tolerance level. <

To simplify things, the tolerance level is directly chosen to be twice the noise. Thus, a value is called statistically significant if it differs from the model at least twice as much as the majority of the remaining values.

Since a detailed description of the analyses of all three series of measurements would go beyond the scope of this article, and the procedure is identical for each trend, only the analysis of the retracements for the secondary trend (scaling 1) will be presented. In order to reveal similarities and differences between the three trend classes as well as to be able to evaluate and put the results into context, exceptions will be made, however.

Based on the retracement distribution read of the histogram (Fig. 3) and the cumulative probability (Fig. 4), some empirically acquired insights can first be gained. Doing so, it should be noted that Bulkowski found similar results under the assumption that the trend continues (Bulkowski, 2012, p.50–52).

Figure 4. Cumulative probability of the retracements between 0 and 1 for scaling 1 (black curve). The blue curve is the conditional cumulative probability with the condition that the retracement is not larger than 100%.



To cover the secondary and tertiary trend in the following presentation of results, the acronym "spt" (the statement is the same for primary and tertiary trend) is used if the results are approximately identical (±1%) for all three trend classes. Otherwise, the primary trend is denoted by *"P"* and the tertiary by *"T"*.

1. **Bisection:** The area with the highest probability of reversal is around the 50% retracement. Furthermore, the probability that the reversal happens until the 50% level is 23% (spt).
2. **Trisection:** The probability that the reversal does not occur before the 33, 33% level is 91, 3% while it is 36, 6% that it does occur before the 66, 67% level (spt).
3. **Fibonacci:** The probability that the reversal is greater or equal $F_2 \approx 38, 2\%$ is 86, 6% (P: 81%, spt otherwise) and that it is smaller or equal $F_1 \approx 61, 8\%$ is 33, 0% (spt).
4. **Trend-preserving:** The probability that an active trend continues (reversal before 100%) is 58, 7% (spt).
5. **Reversal:** The mean of the reversal is 112% (P: 115%), the median is 85% (spt). With the probability of 5% the retracement is smaller or equal to 25% (P: 28%, spt otherwise), with 50% probability it is smaller or equal to 85% (spt), with 75% probability it is smaller or equal to 137% (spt), with 90% probability it is smaller or equal to 206%, and with 99% probability it is smaller or equal to 460%.

6. The probability that, after overstaying the 66, 67% level, the trend will break, i.e., the actual retracement will be greater than 100%, is 65, 1% (spt). Already when passing the 43, 3% level, the trend is more likely to break than to continue (P: 46, 5%, spt).
7. Under the assumption that the trend continues (retracement less or equal to 100%), the probability is 83, 9% (P: 86, 1%, spt) that the retracement is at least 33%. Under the same assumption, the probability is 62, 6% that the retracement is less or equal to 66, 67% (spt).

Still under the assumption that the trend continues, the retracement is at least 25% resp. 15% with a probability of 92, 0% (P: 93, 6%) resp. 98, 0% and with a probability of 73, 3% (P: 74, 8%) resp. 84, 8% at maximum 75% resp. 85% (spt).

So, the first interesting observation is that these statements are **independent** from the trend class. With other words, the underlying distribution is basically **scaling-invariant**.

Next, an example of how these empirical probabilities enable us to verify commonly accepted statements in the field of technical analysis will be given. In particular, the last results will be compared to some of Murphy's (1999, chap. "Percentage Retracements").

- Murphy consciously does not differentiate between trend classes for his statements. The observation above confirms this approach. Around the 50% retracement, the probability of reversal is indeed largest, as stated by Murphy (see 1 above).
- The 33% resp. 38% level fits for 91% resp. 87% of all observed cases as minimal retracement level. Murphy's statement that the usual minimal retracement is 33% can therefore be confirmed, too.
- The statement that the usual maximal retracement is 67%, however, cannot be confirmed since only 36, 6% of all retracements are less or equal to 67% (see 2 above). Even under the condition that the trend continues, i.e., only retracements smaller than 100% are considered, the result is not convincing (see 7 above).
- After breaking the 67% retracement level during the correction, the trend is, as stated by Murphy, indeed more likely to break (see 6 above).

Conclusively, in spite of the fact that four of five of Murphy's statements could be empirically verified, this does not by implication mean that these specific retracement levels are statistically significant, too. Observation 7 even encourages the approach to base the level of minimal and maximal retracement on the personal view ("How much more likely should it be for the trend to break than to continue to fit best into my setting?"). This means that no particular level is a priori extraordinary appropriate. Instead, one should consider using Figure 4 to find the retracement level fitting properly into one's setting.

In an endeavor to resolve the significance issues, the histogram will be analyzed in greater detail in the following.

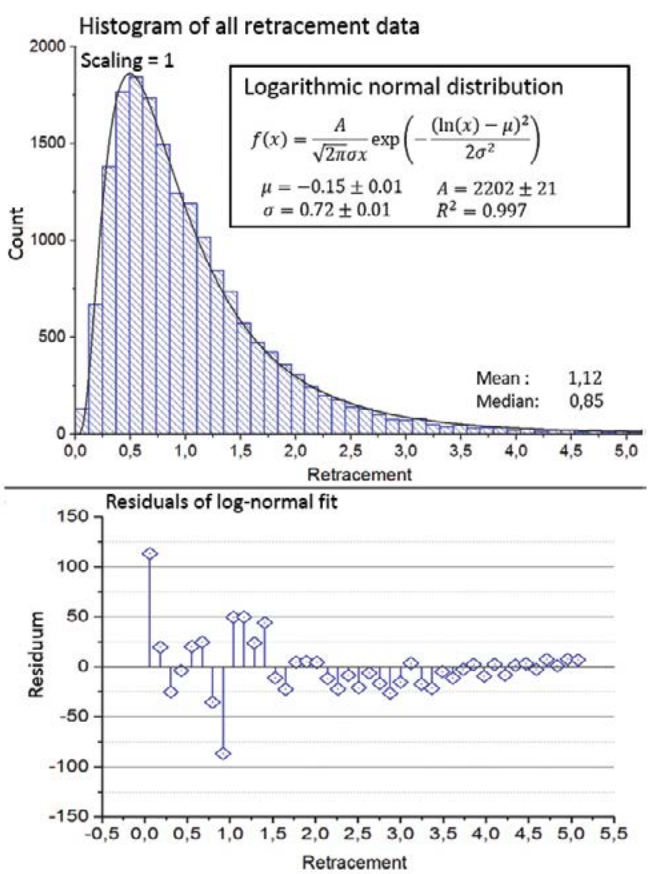
Analysis, distribution function

The goal is to understand the retracement distribution and scrutinize specific retracement levels that are commonly used within technical analysis. As a first step a matching probability density function will be fitted to the histogram. Based on the shape of the measured distribution, the gamma (Georgii, 2012, p. 43), the beta (Georgii, 2012, p. 45), and the logarithmic normal distribution (Limpert et al., 2001) come forward. While all three fits show a good R^2 value, the gamma as well as the beta distribution are dropped out because of strong systematics observed in the residuals (spt). So, the logarithmic normal distribution is chosen, even though a systematic behavior of the residuals cannot be certainly excluded for the logarithmic normal fit (see Figure 6, decreasing for increasing scaling).

The resulting probability density functions for the three trend classes are very similar. This confirms the already observed phenomenon of the market's scaling invariance. The logarithmic normal distribution also occurs in the field of mathematical finance, especially with regard to stock prices. In particular, the *Black-Scholes model*, which is used to price options (Scholes and Black, 1973), is based on the assumption that the stock prices follow a geometric Brownian motion. This leads to a logarithmic normal distribution of the relative stock price changes (Øksendal, 1999).

In the residuals (Figure 5), a big spike at the 0% and 100% retracement is evident. This observation motivates the empirical examination of the significance of common retracement levels.

Figure 5. Retracement distribution and logarithmic normal fit with residuals for scaling 1 and bin size 0, 12.



Analysis, significant levels

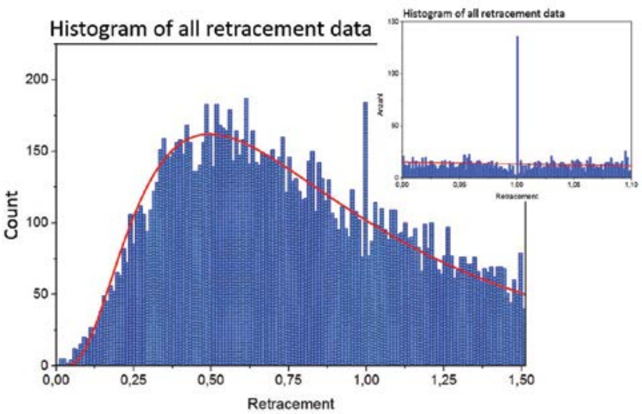
With the bin resolution of Figure 5 (bin size is 0, 12), only the mentioned differences in 0% and 100% are immediately observable. However, the differences are not big enough to be statistically significant (Def. 2) when considering this bin resolution. This leads to the conclusion:

3. Observation

No retracement levels are statistically significant for bin resolutions smaller than 0, 1 = 10%. <

This observation also applies to the other trend classes. For a higher resolution, however, this could change. Therefore, a histogram with a higher resolution (Figure 6) is examined. Now, the 100% retracement clearly has a significantly higher count than the other surrounding retracement values. This phenomenon can also be seen for the tertiary trend, for which the 50% retracement is also significant. For the primary trend, on the other hand, there are no such peaks visible. Concluding, it can be recorded:

Figure 6. Histogram of the retracement data between 0 and 1, 5, secondary trend (scaling 1), with a total of 142 bins and a bin size of 0, 01. Also shown is a high resolution picture (bin size ≈ 0, 001) of the environment of 1.



4. Observation

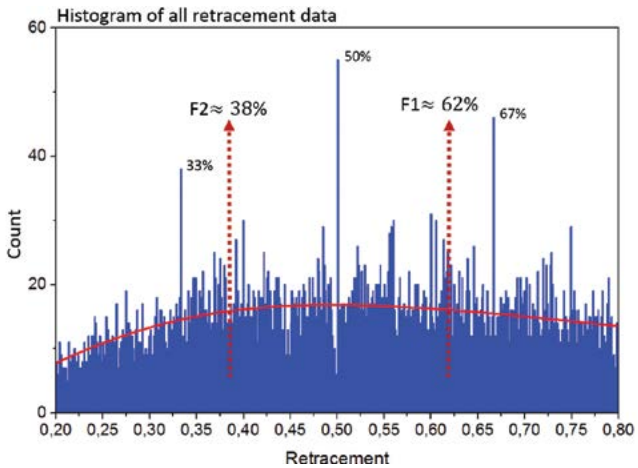
For resolutions smaller than 0, 01 = 1% there are no statistically significant retracement levels for primary trends. The 100% retracement level is significant for the secondary and tertiary trend with the 50% retracement being also significant for the latter one.

In the case of the secondary trend, no clear statements can be made for the other levels mentioned by Murphy. Thus, the resolution is increased again to higher than 0, 001 = 0, 1% (see Figure 7). Now, there are three significant pikes clearly visible. The same can be observed for the tertiary trend, but again, not for the primary. In particular, several significant pikes for the tertiary trend can be detected, but only one at the 100% retracement for the primary trend (for the first time).

5. Observation

For resolutions higher than 0, 001 = 0, 1% the 100% retracement level is significant for the primary trend. Furthermore, the 33, 3%, 50% and 66, 7% levels are statistically significant for the secondary and tertiary trend.

Figure 7. Histogram of the retracement data between 0, 2 and 0, 8, secondary trend (scaling 1), with a total of 542 bins and a bin size of approx. 0, 001.



The importance of the last observations (3–5) for the field of technical analysis will be illustrated in the following.

While even with a resolution of 0, 1% the Fibonacci retracements are **not** significant for any trend class, the other considered retracement levels are indeed significant for at least one combination of resolution and trend class. Thus, there is **no** empirical basis for excelling the Fibonacci retracements over any other retracements. Furthermore, the significance of the other considered retracements highly depends on the combination of trend class and resolution. The higher the resolution and the more minor the trend, the more significant are the levels in ascending intensity. This particular market characteristic, therefore, is not scale-invariant but the exact opposite. One possible explanation for this observation could be that the common retracement levels are self-fulfilling prophecies (see Murphy, 1999, "The Self-Fulfilling Prophecy"; Merton, 1948). While the idea of Fibonacci retracements seems not to have yet spread enough to have an impact, the concept of correction trisection and the 50% and especially the 100% level were already introduced by Dow and later taken up by Murphy. Therefore, these specific retracement levels are well-known to many market participants that act accordingly. This does not affect the market seriously, however, but is limited to an environment of the corresponding level as well as to a time environment (secondary and tertiary trends). This short-term character also indicates a self-fulfilling prophecy because a fundamental market characteristic would affect primary trends, too. Indeed, only the effect of the 100% retracement level can be observed for all trend classes. Even though the significance strongly decreases for superior trends, it is observable in an environment of ±10% around 100% for short-term trends. One possible explanation for this phenomenon could be the big players' activities, i.e., market participants that visibly affect the market itself when opening or closing a position.

Assuming that the intention of these big players is basically to gain profit, it is advisable for them to not reveal one's actions immediately. Simply buying and selling whole positions at once would affect the market prices to their disadvantage. A significant price drop for a large open position could be fatal.

According to the profit gaining intention, it would make sense for these big players to use their market impact to their favour instead. In other words, in the case of an imminent trend break (100% retracement), they could artificially prolong the trend, thereby avoiding the risk to lag the closure of their market position and open the possibility of selling their position without excessive slippage after a market slowdown.

Conclusion

At the end of this article, all key statements that have been empirically deduced will be summarized once again.

- The basic retracement distribution is scale-invariant.
- The retracement is log-normally distributed for all trend classes. There is a connection to the Black-Scholes model and the postulated geometric Brownian motion for the stock returns there.
- Price reversal is most likely around the 50% retracement (Figure 5).
- Trend correction is more likely than trend break (independent of trend class).
- No empirical reason for restricting to a few distinguished retracement levels found (see 3). In particular:
  - 100% retracement not empirically verified as support level due to the fact that no clear statistical significance for any trend could be observed (see 3).
  - Significance of the Fibonacci retracement for every trend class and bin resolution up to 0, 1% empirically refuted.

However, the 100% level does show significance in a small environment (the size of the environment depends on the trend class and decreases with increasing trend duration). The same applies to the 33%, 50% and 67% level for secondary and tertiary trends.

On the one hand, statements about the basic statistic distribution are scale-invariant in essence. On the other hand, statements concerning the difference from this distribution are strongly trend-correlated with the rule: the longer the trend the fewer statistical pikes.

When choosing a retracement forecast (i.e., forecasts of the minimal and maximal retracement), the optimal level should be chosen according to the individual requirements and with the help of the cumulative probability (Figure 4). If the chosen level lies around 100%, the local significance of the 100% retracement should then be considered. The same applies to the 33%, 50% and 67% retracement for secondary and tertiary trends.

Final considerations

The empirical studies in this article have debunked the myth of Fibonacci retracement to be human (made). Furthermore, it has been shown that retracement forecasts can be optimized with the help of empirical analyses. Even though Murphy's advices have been proven to be mostly an appropriate choice the (cumulative) probability distribution that was found creates added value. Also, the empirical proof of scale-invariance of the retracement distribution improved the market understanding. Further understanding can be achieved by answering new questions that have been aroused by the discovered logarithmic normal distribution and that would not have been asked without an empirical analysis—first and foremost the question of the parallel to the Black-Scholes model.

Regardless of any particular results, this article has shown the utility of empirical studies and a scientific approach in the field of technical analysis.

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Backtest of Trading Systems on Candle Charts

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Abstract

In this paper, we try to design the necessary calculation needed for backtesting trading systems when only candle chart data are available. We lay particular emphasis on situations that are not uniquely decidable and give possible strategies to handle such situations.

Introduction

For at least a decade, more and more software solutions for self-designable trading systems have emerged (e.g., Ninjatrader, Tradestation, Tradesignal online, Nanotrader, Investox). All of the examples listed also incorporate a backtesting (also called historical simulation) tool that includes helpful statistical data on the trading success (i.e., it is possible to run a trading system on historical data to simulate the trades). The idea is that trading systems that were successful in the past should also be successful in the future. Analogously, a trading system that performs poorly on historical data cannot be trusted and is supposed to be unsuccessful in the future. This makes backtesting an important tool for designing trading systems.

Although already on the market for several years, we found that many of the software solutions perform calculations sometimes incorrectly. This concerns even situations that are uniquely decidable. When backtests are evaluated just on the knowledge of candle data, however, there are always situations that cannot uniquely (SNU: situation which is not unique) be determined, see e.g., the book of Pardo [2008, Chapter 6, Section "Software Limitations"] or Harris [2008, Chapter 6]. Pardo (2008) and Harris (2008) describe this problem but do not discuss the backtest algorithm itself and how to deal with such problems. The least a backtest engine should do in these situations is to warn the user about these problems. Also, the user should be informed about how such situations are handled. We suggest that there should be four different strategies to choose from:

I. Worst case (wc): the SNU is evaluated as the worst possible case for the user.
II. Best case (bc): the SNU is evaluated as the best possible case for the user.
III. Ignore (ig): the entry signal or the whole trade is ignored.
IV. Exact (ex): to resolve the problem, more data (sometimes even tick data) have to be loaded.

To the best of the author's knowledge, there is no publication about backtest algorithms alone, only for the statistical evaluation of backtests. Typical statistical measures like Sharpe ratio, average trade, profit factor, and many others, see e.g., [Kirkpatrick and Dahlguist, 2011, Chapter 22], give hints on how the trading system performs.

Therefore, we discuss the procedure of backtest evaluation based on candle/bar chart data in detail. Further information about backtesting and some limitations can be found in the books of Chan [2009, Chapter 3], Pardo [2008, Chapter 6], and Harris [2008, Chapter 6], and for trading options, in the book of Izraylevich and Tsudikman [2012, Chapter 5].

It is well known that a backtest is just a simulation over the past and does not predict future behavior of a trading system. The ability to accurately simulate a parameter-dependent trading system on some chart data can rapidly lead to an overestimation of the parameters by optimizing these parameters to reach the best performance on the historical data. Ni and Zhang [2005]present a method to improve the efficiency of backtesting a trading strategy for different parameter choices, but they do not explain the backtest evaluation itself. The result could be an optimal trading system but only well adjusted to the past. In general, this does not mean that this parameter setting is also appropriate in the future and gives a stable strategy. In contrast, this can lead to tremendous losses. This phenomena is called backtest overfitting, see [Bailey et al., 2014a, b; Carr and de Prado, 2014.] and also [Pardo, 1992, Chapter 6] for a detailed discussion. Therefore, backtesting needs to be used carefully but, nevertheless, gives important information about a trading strategy.

Clearly, the above remarks and references show that a correct interpretation of backtest results is a difficult and more or less up to now unsolved problem. However, this is not the subject of our considerations in this paper. Here, we want to focus the attention on how the backtest evaluation itself has to be calculated correctly.

Due to symmetry, it suffices to consider entry orders for long positions only. Therefore, we discuss only long positions unless we explicitly refer to short orders. Since market orders are to be executed at the open of the next candle, problems of backtest evaluation for the position entry only occur for "limit buy" (with limit level l^*), "stop buy" (with stop level b^*), and "stop limit buy" (with stop level b^* and limit level l^*) long orders. (See e.g. [Pardo, 1992, Chapter 4] for definitions of some order types.)

We discuss the principal part of this paper (i.e., the decisions for backtest evaluation) in the section "Backtest evaluation algorithm," while in the subsection "Assumptions and limitations", we need to make some assumptions and discuss some limitations of a backtest. In the subsections "Entry of a long position with 'limit buy' order," "Entry of a long position with 'stop buy' order," and "Entry of a long position with 'stop limit buy' order," we discuss when and how a position has to be opened with the classical "EnterLongLimit()", "EnterLongStop()"

and "EnterLongStop- Limit()" orders, respectively. In all three cases, the decision tree is only given for the first bar of the trade. Because a trading setup typically includes immediate stop losses (at s^*) or target levels (at t^*), even in the first bar besides the pure position entry, there are numerous other things to check. Once the first bar of the trade has finished, or in case we enter the position immediately at the beginning of the period, the decisions for such an active position in succeeding bars is simpler. The decision tree for the latter is given in the subsection "Exit from an active long position." We close the discussion with the Conclusion.

Backtest evaluation algorithm

We look at situations for different entry and exit setups. All orders are generated at the end of a candle so that these orders can be filled in the next candle. Therefore, we take a look at this next candle for different orders. The examined candle has four values: H = High, L = Low, O = Open, and C = Close.

Assumptions and limitations

To be able to perform exact calculations, we first need to make a continuity assumption on the price evolution within a candle.

Assumption 1. (No intra-period gaps)

We assume that the price evolution inside the period skips no nearby tick-values, i.e., starting at the open until the end of the period at the close, all price moves during that period (up or down) come only as ± 1 tick. Intra-period gaps, i.e., moves by more than one tick, thus are not allowed.

This assumption is essential for determining intra-period entry or exit prices (e.g., at limit or stop levels). In live trading, however, this assumption is not realistic. To overcome this problem, usually slippage is introduced for each backtest trade, see e.g., the book of Pardo [2008, Chapter 6, Section "Realistic Assumptions"] for a detailed discussion.

Additionally, we need to assume that all orders are filled at the requested price.

Assumption 2. (Market liquidity)

We assume that we trade on a perfectly liquid market (i.e., our orders do not affect the price changes and are completely filled at the corresponding entry or stop level).

Of course, this assumption is also not realistic. Similar to Assumption 1, slippage can help to get more reasonable results.

Since all prices (measured as tick-values) are integers, we need to make sure that all values given by the user (like limit level l^*, etc.) are of the same type to avoid rounding errors, see also [Pardo, 2008, Chapter 6, Section "Software Limitations"].

Assumption 3. (Rounded values)

All values such as limit price, target, and stop loss level are given as numbers rounded to the corresponding next possible price value, which depends on the tick size.

For long positions, the stop level b^* for stop buy order and the target level t^* are rounded up, while the stop loss level s^* and limit price l^* are rounded down.

For short positions, the stop level b^* for stop buy order and the target level t^* are then rounded down, while the stop loss level s^* and limit price l^* need to be rounded up.

This way to round the values does not change any decision during the backtest evaluation, but it corrects the price values used for the computation of the outcomes of each trade.

In case the long position is coupled with a stop loss order (stop level s^*) or a target order (target level t^*), we always assume $s^* < l^* < t^*$ and $s^* < b^* < t^*$.

Next, we need to simplify the best and worst case for SNUs. Suppose we are invested in a stock, and there is a SNU with the two options of 1) exit the position at target level t^* or 2) stay invested. Of course, exit at t^* should immediately lead to a win trade. However, if we change the target in the next period, it is possible to earn even more money if we do not exit the position at this moment but later in one of the subsequent candles. This can also affect upcoming trades, which in general depend on the current status (invested or not invested) and thus can increase the complexity of the decisions needed to be made for the real (globally) best case. Therefore, we always choose the simplest setting, which is best for the user at the current period. In this easy example, this would be to immediately exit the position at target level t^*.

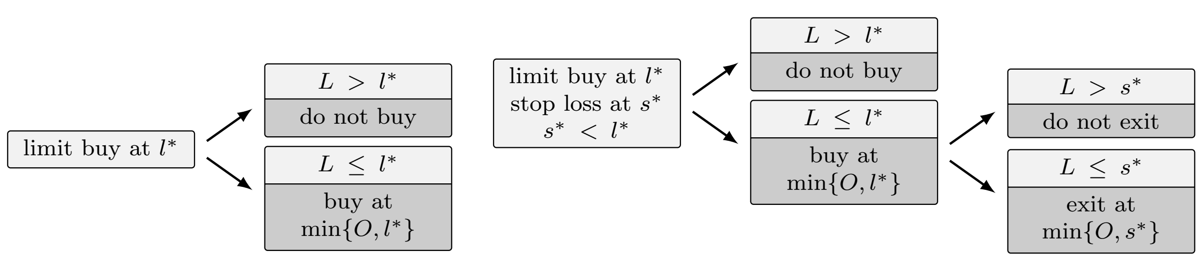
Assumption 4. (Worst and best case)

Best and worst case decisions in situations that cannot be uniquely determined (SNU) should be made on the premise that it is best/worst for the current period only.

Entry of a long position with "limit buy" order

Here, the long position is only opened once the price reaches the limit level l^* (or below). This is the situation of an entry with the classical "EnterLongLimit()" order optionally supplemented by stop loss s^* and target levels t^*. We assume $s^* < l^* < t^*$. The decision trees are shown in Figures 1 through 3.

Figure 1. Entry setups with limit buy long order.



(a) Only limit buy long order. (b) Limit buy long order supplemented with stop loss.

Figure 2. Entry setup with limit buy long order supplemented with target.

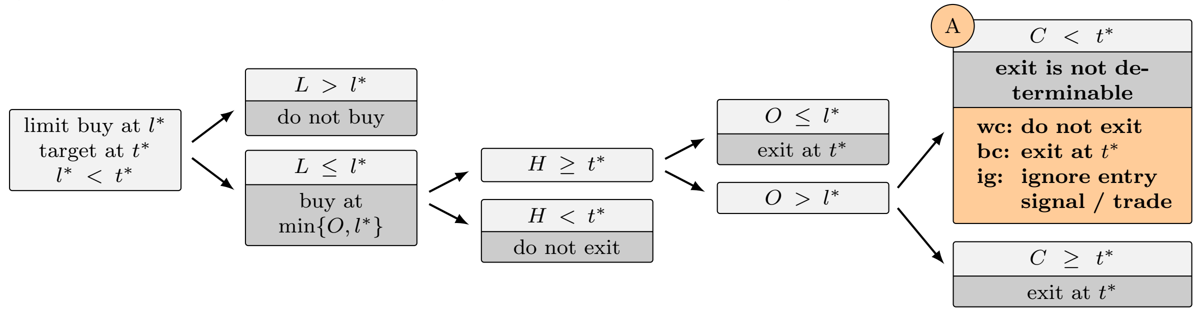


Figure 3. Entry setup with limit buy long order supplemented with stop loss and target.

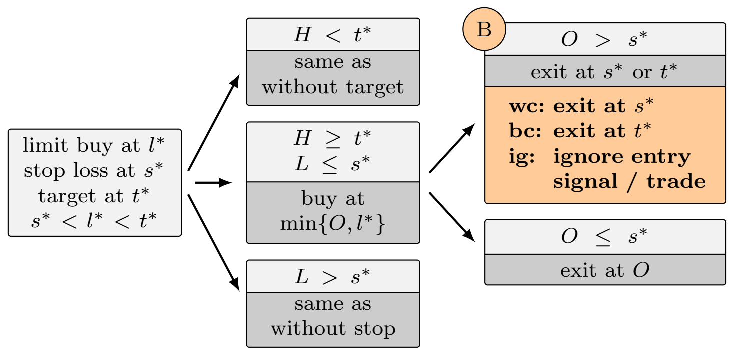
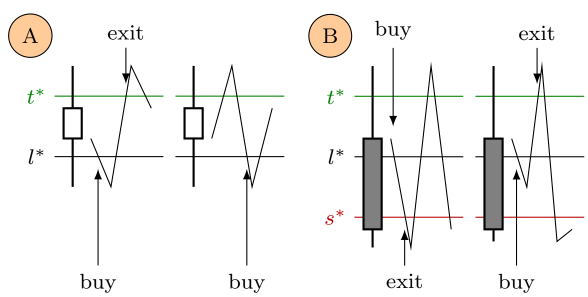


Figure 4. Variations of possible price development within a candle for SNU with limit buy long order.



(a) Cases for Figure 2. (b) Cases for Figure 3.

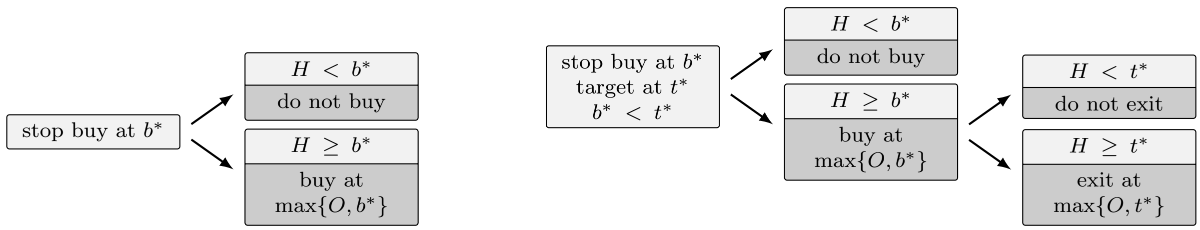
In Figures 2 and 3, the cases marked with A and B, respectively, are two SNUs (i.e., if we cannot load extra data like tick data to make these situations unique, there are multiple possibilities for the correct position entry and/or exit). Figure 4 shows one example for each possibility for both SNUs A and B.

We always assume $s^* < l^*$ because of the following reason: In case $s^* \geq l^*$, the position would be closed right after it is opened, which makes no sense and should therefore be forbidden by the software (i.e., these orders should be canceled/ignored).

If $t^* \leq l^*$, the same would happen if $O \geq t^*$ and of course $L \leq l^*$. However, if $O < t^*$, the position would be opened at the beginning of the period, which is equivalent to a market order executed at the open of the subsequent period. In this case, the trade would not immediately be stopped and thus can be handled as in the subsection "Exit from an active long position" if it is not ignored in advance.

From the decision trees in Figures 1 through 3, we see that for limit orders, only a combination involving a target where the target is reached in the entry period leads to SNUs. If there is no target or if the target is far away, all situations are uniquely decidable.

Figure 5. Entry setups with stop buy long order.



(a) Only stop buy long order. (b) Stop buy long order supplemented with target.

Figure 6. Entry setup with stop buy long order supplemented with stop loss.

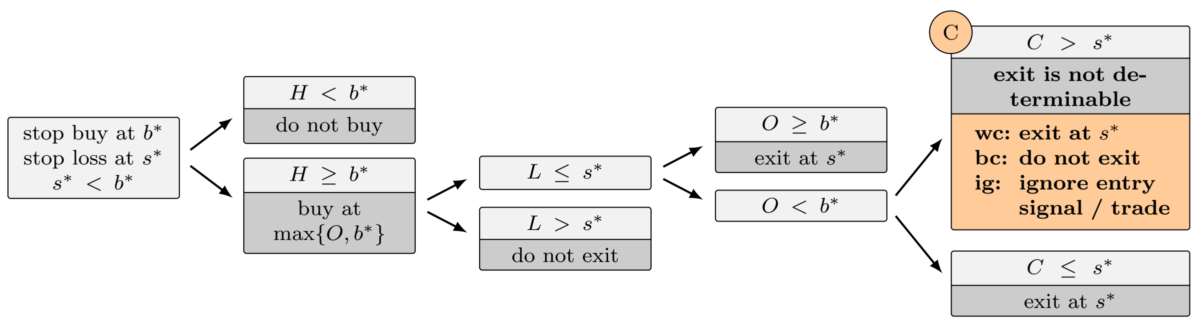


Figure 7. Entry setup with stop buy long order supplemented with stop loss and target.

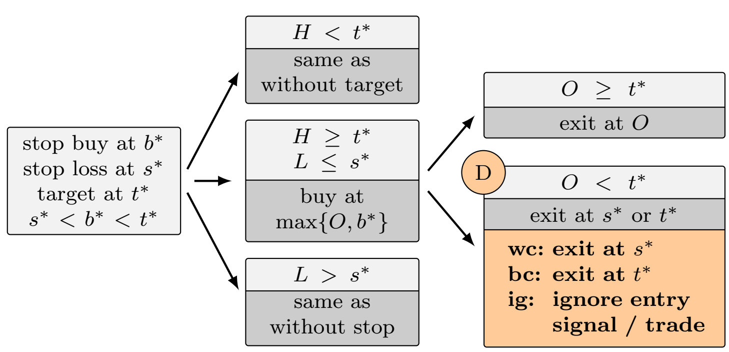
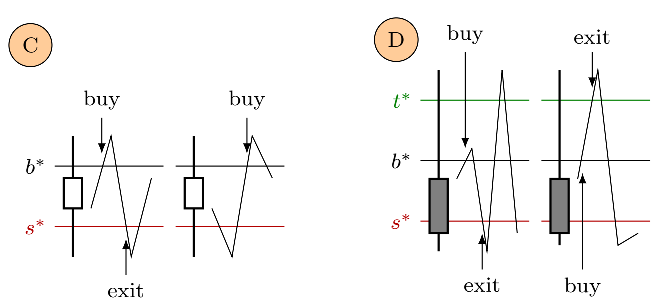


Figure 8. Variations of possible price development within a candle for SNU with stop buy long order.



(a) Cases for Figure 6. (b) Cases for Figure 7.

Entry of a long position with "stop buy" order

Here, the long position is only opened once the price reaches the stop level b^* (or above), created by the classical "EnterLongStop()" order. Again, the order can optionally be supplemented by stop loss (s^*) and target levels (t^*) with $s^* < b^* < t^*$. The decision trees are shown in Figures 5 through 7, and the examples for the SNUs are in Figure 8.

Since an entry stop order is some kind of mirrored version of the entry limit order, we now have SNUs for the entry stop order supplemented with an initial stop loss level.

Again, the case $t^* \leq b^*$ makes no sense, because the position would be closed immediately after the opening, compare the case $s^* \geq l^*$ for long limit order.

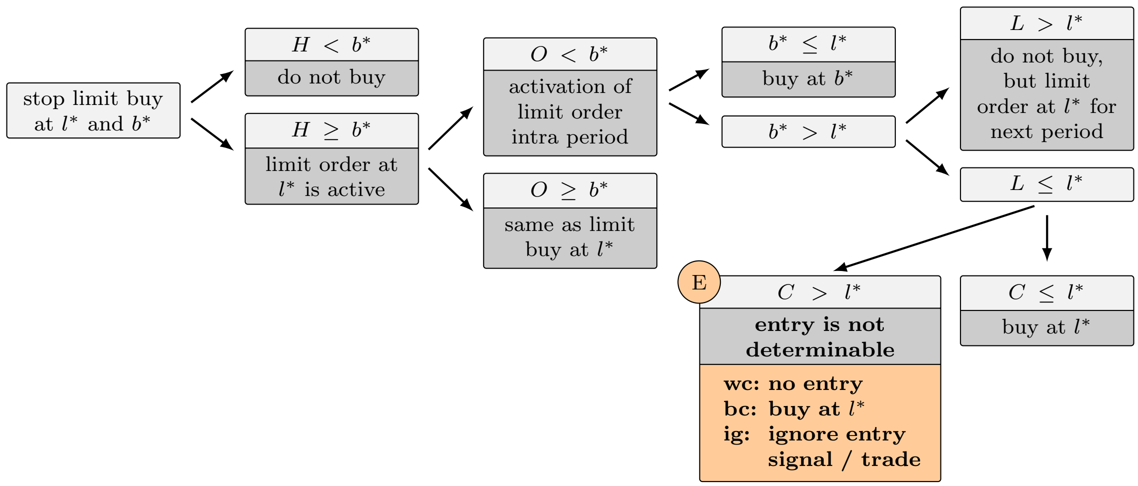
In the case $b^* \leq s^*$ the position is either to be closed after opening if $O \leq b^*$ or, if $O > b^*$, we have an equivalent case to a market order.

Entry of a long position with "stop limit buy" order

Here, a limit buy order at level l^* is only generated once the price reaches the stop level b^* (or above), as is generated by the classical "EnterLongStopLimit()" order. [i.e., the trader in principle wishes to have an "EnterLongLimit()" order at level l^*, but to activate that order he first wants the prices to reach the stop level b^* (or higher)]. Again, this order may optionally be supplemented by stop loss (s^*) or target levels (t^*). We assume $s^* < \min\{l^*, b^*\} \leq l^* < t^*$.

The decision trees are shown in Figures 9 to 12, and examples for the SNUs in Figures 13 to 16, respectively.

Figure 9. Entry setup with stop limit buy long order.



This entry order type is much more complex and therefore leads to larger decision trees and much more SNUs. Even the worst cases and/or best cases for some SNUs are not uniquely determinable because there are situations where a position can be opened or there is just an active limit order at the end of the candle (see e.g., SNU E). In general, it is not clear whether it is worst or best to have an active limit order or an open position at the end of the candle in such cases. Because of Assumption 4, we decide to measure the quality of an open trade by the current value of the trade, which in this case is the difference between the close of the candle and the entry price of the position. If the close is larger than the entry price, we currently are in a positive trade (and thus the best case), which is better than having just an active limit order (worst case), and vice versa if the close is below the entry price.

Figure 10. Entry setup with stop limit buy long order supplemented with stop loss.

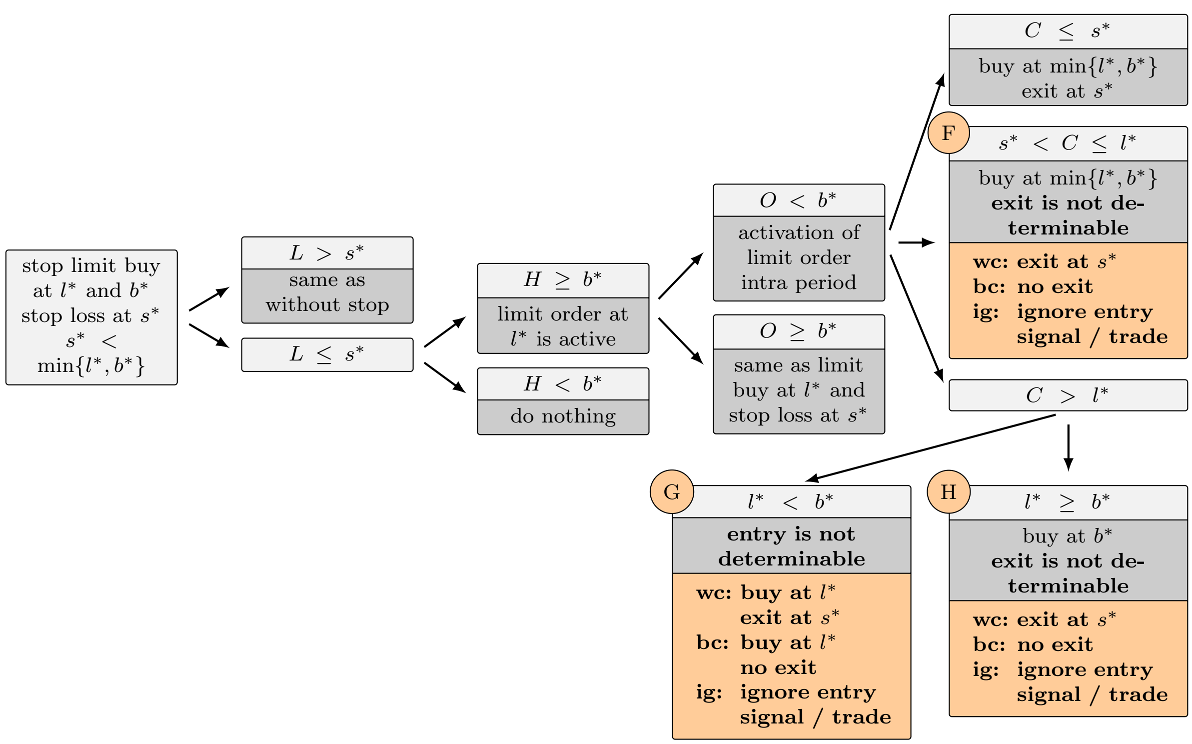


Figure 11. Entry setup with stop limit buy long order supplemented with target.

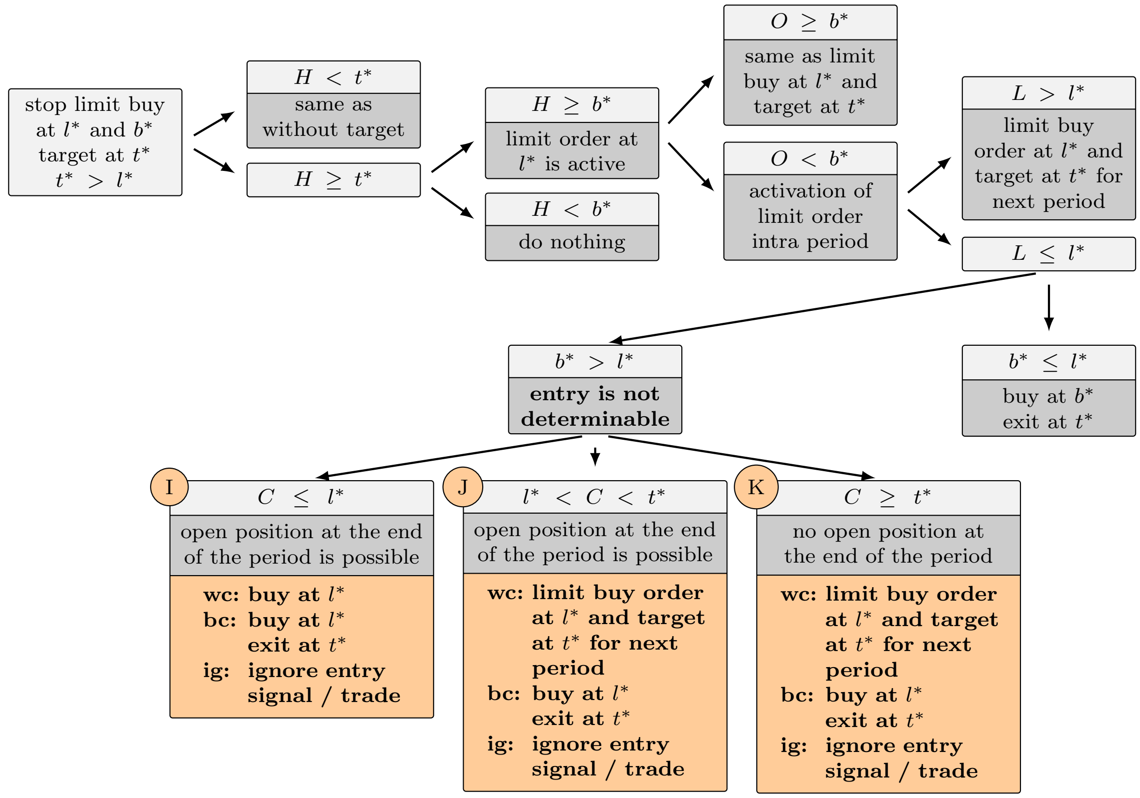


Figure 12. Entry setup with stop limit buy long order supplemented with stop loss and target.

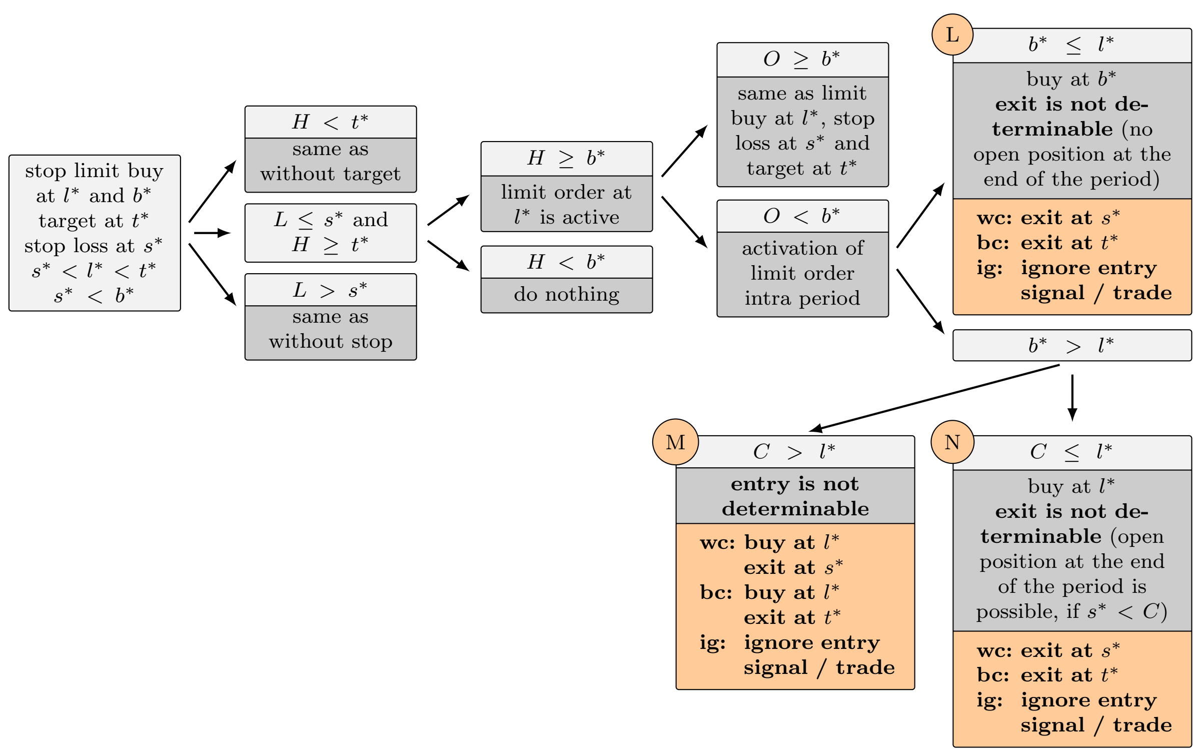


Figure 13. Variations of possible price development within a candle for SNU with stop limit buy long order for Figure 9.

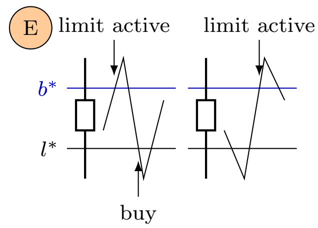


Figure 14. Variations of possible price development within a candle for SNU with stop limit buy long order for Figure 10.

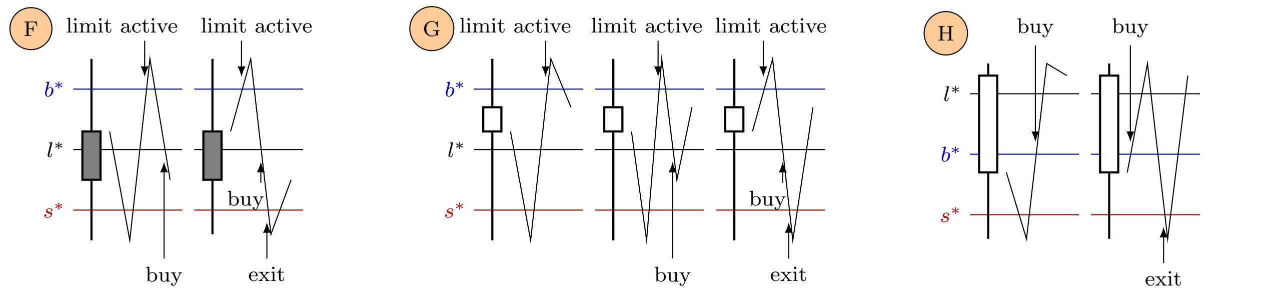


Figure 15. Variations of possible price development within a candle for SNU with stop limit buy long order for Figure 11.

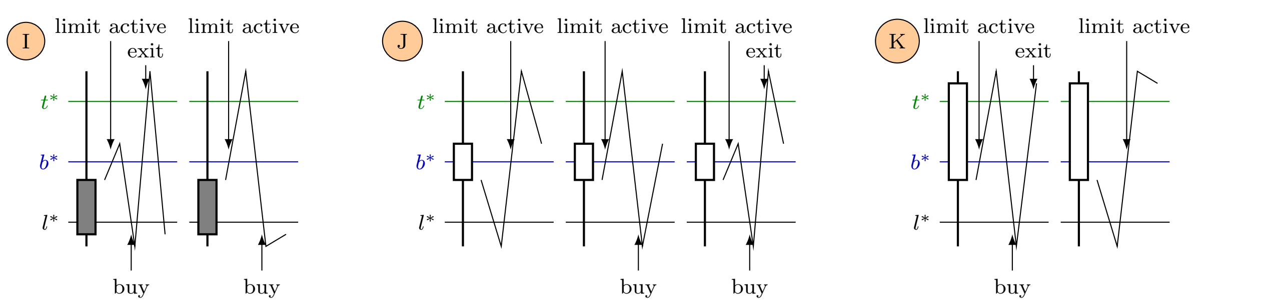
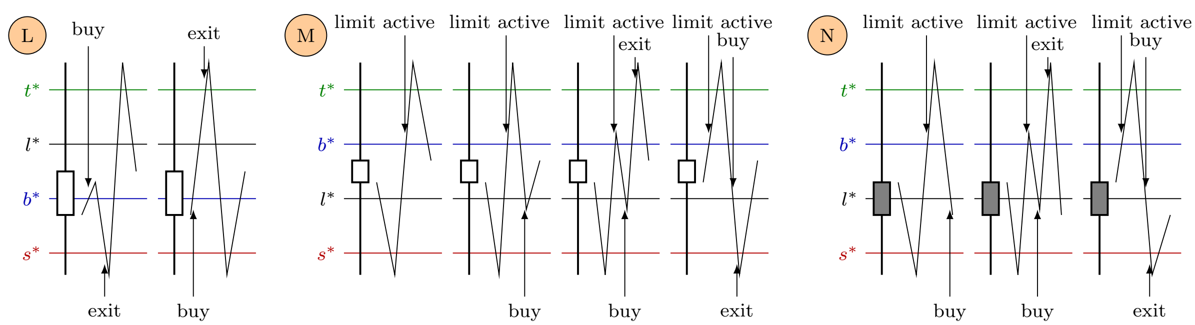


Figure 16. Variations of possible price development within a candle for SNU with stop limit buy long order for Figure 12.



Exit from an active long position

The final discussion deals with the case of an active long position (i.e., at the end of the prior period a long position remained open). This also includes situations where a market order was generated in the prior candle such that a long position is opened right at the open of the current period. The decision trees for the current period are shown in Figures 17 and 18 and the examples for the SNUs in Figure 19.

Figure 17. Exit setups during an active long position.

(a) Only stop loss. (b) Only target.

Figure 18. Exit setup during an active long position with both stop loss and target.

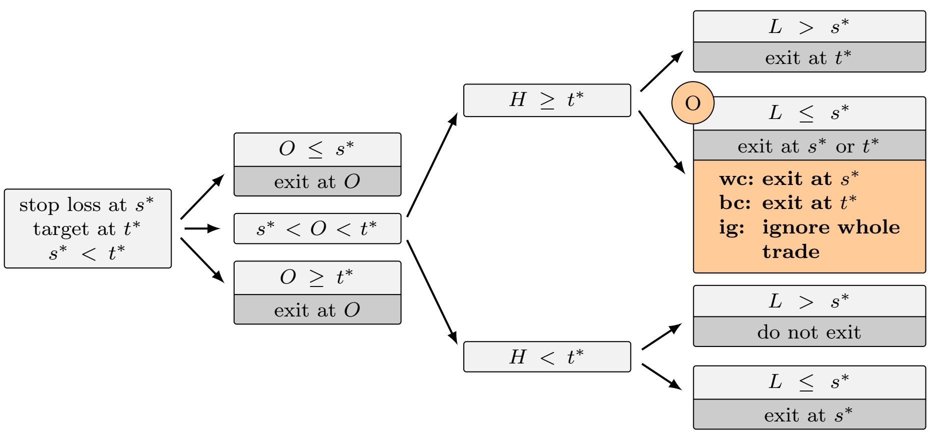
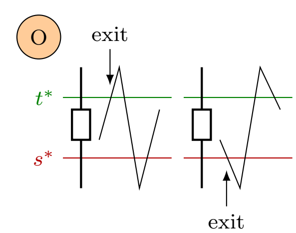


Figure 19. Variations of possible price development within a candle for SNU during an active long position for Figure 18.



Conclusion

The precise listing of the backtest evaluation algorithm in the preceding section shows very clearly that not uniquely decidable situations (SNUs) are omnipresent when only candle data are available. This is not consistent with the fact that widespread software solutions ignore that problem completely. An honest evaluation should give users the choice of worst/best case calculations. Future software solutions should be able to reload finer candle or tick data for the bars in question in order to evaluate backtests exactly.

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Do Ichimoku Cloud Charts Work and Do They Work Better in Japan?

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Abstract

This article explores the profitability of signals generated using Ichimoku cloud charts on single stocks in Japan and the United States. We construct a conservative and aggressive long-only and short-only strategy over a period from 2005–2014 and examine the profitability of the various strategies. Based on the simulation, we evaluate the ability of Ichimoku cloud charts to generate profitable trading signals in these two markets. In addition, we propose that the cloud chart exhibits characteristics typical of a momentum and breakout strategy, with returns that are positively skewed and with a small left tail due to the natural stop loss built into such a strategy.

Introduction

Ichimoku Cloud Charts

Candlestick charts have existed in Japan since the 18th century, but it was the time just before World War II that Goichi Hosoda, a journalist using the pseudonym Ichimoku Sanjin (Ichimoku meaning 'at a glance' in English), combined moving averages with candlestick charts to improve the strength of his technical analysis. Then, in 1996, Hidenobu Sasaki, who was working at Nikko Citigroup Securities, revised his method and published *Ichimoku Kinko Studies,* which formed the current methodology of the cloud chart analysis. Having been voted the best technical analysis book in the Nikkei newspaper for nine years repeatedly, this method is still considered one of the most common technical analyses in Japan.

Key Research Questions

In this study, we aim to apply the original specification for the cloud charts to single stocks in the United States and Japan. We design a simple trading strategy based on basic implied predictions from the cloud charts and use the profitability of the various strategies to evaluate its effectiveness. Through this study, we hope to shed some light on three key research questions:

1. *How would a simple trading strategy constructed using signals from the cloud chart perform when applied to individuals stocks?* We examine the profitability of the various strategies when compared to a strategy that simply holds or shorts the stock. In addition, we use the information ratio as a way to provide a rough measure of the different strategies' ability to add value.

2. *Do the results differ based on the market environment?* Momentum strategies typically perform best in scenarios where there is a definitive trend, such as following a crash or in a strong bull market, and have a weaker performance when prices move within a range bound environment. We examine the performance of the basic strategy over different market environments to try to identify which environments are more favourable for the use of cloud charts.

3. *Do results vary relative to geographic position?* As Cloud Charts are a tool that was first introduced in Japan and only brought to the West many years later, we thought it would be interesting to investigate if the performance of the strategy differed when applied to stocks in these two countries. One possible argument against the persistence of any performance would be that if the strategy performs better in Japan, the tools main user base, this could be evidence for the self-fulfilling hypothesis commonly levelled as a criticism of technical analysis. Hence, such an investigation can also serve as a simple robustness check of the results and can provide some high-level insight into the possible persistence of any observed outperformance.

Ichimoku Cloud Chart Construction

Ichimoku cloud charts are constructed from five lines: the Tenkan line, Kiniu line, Senkou span A, Senkou span B and Chikou line. Figure 1 provides a graphical illustration of an Ichimoku cloud chart with the various lines of interest plotted on the chart.

The Tenkan line acts like a moving average. It is calculated by averaging the highest daily high and lowest daily low in a nine-day period.

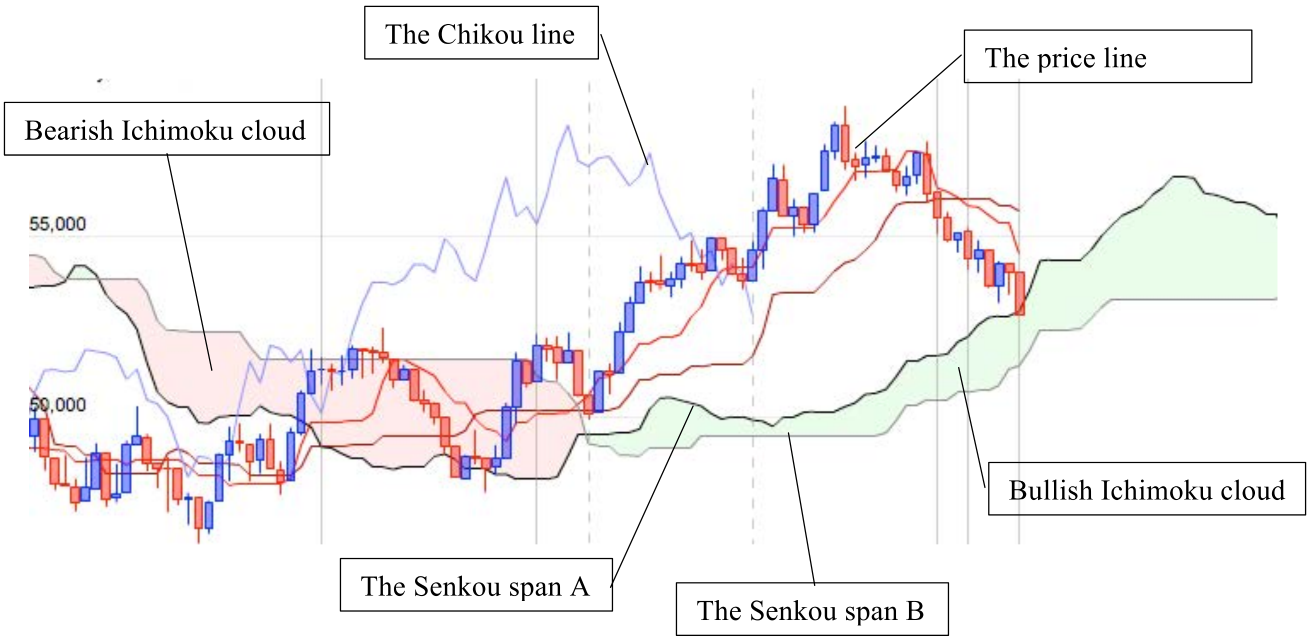
The Kiniu line is very similar to the Tenkan line except that it uses 26 days, which was originally the Japanese trading days in a month.

The Senkou span A and B are utilised to construct the Ichimoku cloud. For the Senkou span A, the midpoint between the Tenkan line and Kiniu line is calculated and shifted 26 bars forward.

For the Senkou span B, the midpoint of the last 52 sessions, which is translated as two trading sessions in the Japanese market, is calculated and shifted 26 bars forward.

The area between the Senkou spans forms the Ichimoku cloud. If span A is higher than span B, this is a bullish signal indicated with green. On the other hand, if span B is higher than span A, it is a bearish signal indicated with red. Lastly, the Chikou line is the price line shifted back 26 sessions, showing a bullish signal when it is above the Ichimoku cloud and bearish signal when it is below the cloud.

Figure 1. Illustration of Ichimoku Cloud Chart



Data Analysis

Data

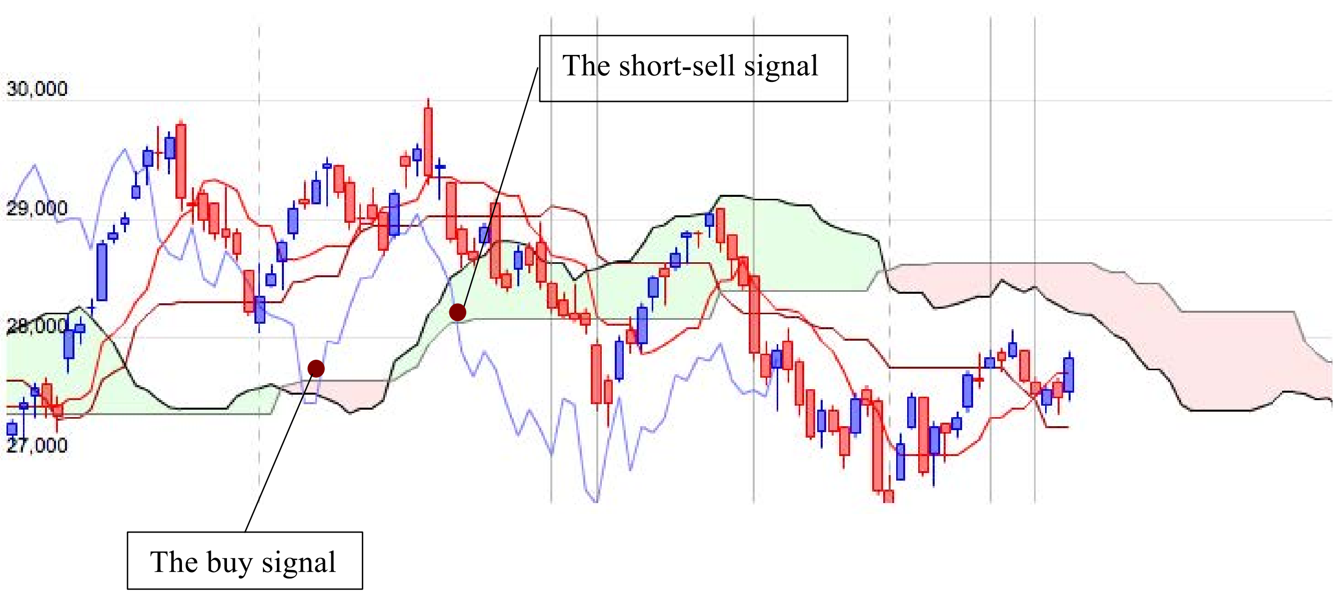
For this study, we used stock prices for the current stocks in the S&P 500 and Nikkei 225 that had data that went back to the start of 2005. For the purpose of the study, we conducted the backtest of the trading strategies over the period from 1 January 2005–31 December 2014, and the sample consisted of 202 stocks in the Japanese market and 446 stocks in the U.S. market.

Description of Key Trading Signals

Although there are different types of signals that can be produced by the cloud charts, anedoctal evidence suggests that the most reliable and consistent one is the Chikou line crossing the Ichimoku cloud. Hence, we have used that as the basis for the generation of signals for the different trading strategies proposed in this paper.

In this paper, we propose series of long-only and short-only strategies based on the crossing of the Chikou line with the cloud. The key buy signal is classified as the Chikou line crossing the higher span of the cloud from below. The key short-sell signal is classified as the Chikou line crossing the lower span of the cloud from above. Figure 2 provides a graphical illustration of the key buy and short-sell signal.

Figure 2. Illustration of Buy Signal and Short-Sell Signal



Implementation of Buffer

It is largely accepted that if price moves within the cloud area, it could represent trading in a range bound environment, leading to false signals that would prove unprofitable. Hence, to reduce the number of false signals around the cloud and to slow down the model, we implemented a 1% buffer around the cloud for the generation of signals. Hence, the Chikou span would have to move 1% higher than the price of the cloud for a buy signal to be triggered and would have to move 1% below the price of the cloud for a short-sell signal to be initiated.

Trading Strategies

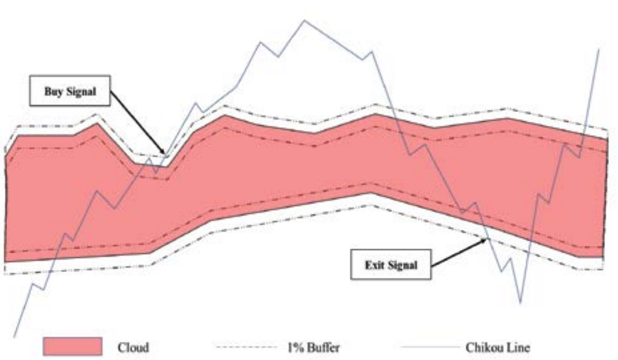
We constructed four different trading strategies for our study: a conservative long-only strategy, an aggressive long-only strategy, a conservative short-only strategy, and an aggressive short-only strategy. The conservative strategies are slower and should capture fewer false-signals, while the aggressive strategies are faster and more reactive to price movements.

Conservative Long-Only Strategy

The rules for this strategy are illustrated in Figure 3 and are as follows:

- Initiate a long position when the Chikou line crosses the top of the cloud from below.
- Close the long position when the Chikou line crosses the bottom of the cloud.

Figure 3. Illustration of Conservative Long-Only Strategy

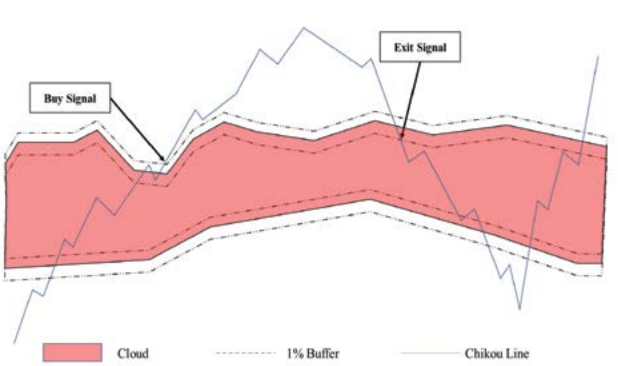


Aggressive Long-Only Strategy

The rules for this strategy are illustrated in Figure 4 and are as follows:

- Initiate a long position when the Chikou line crosses the top of the cloud from below.
- Close the long position when the Chikou line crosses the top of the cloud.

Figure 4. Illustration of Aggressive Long-Only Strategy

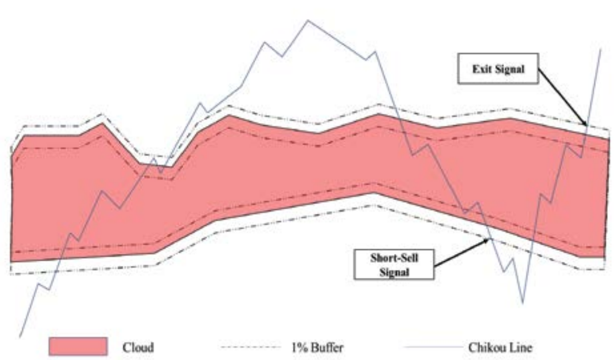


Conservative Short-Only Strategy

The rules for this strategy are illustrated in Figure 5 and are as follows:

- Initiate a short position when the Chikou line crosses the bottom of the cloud from above.
- Close the short position when the Chikou line crosses the top of the cloud.

Figure 5. Illustration of Conservative Short-Only Strategy

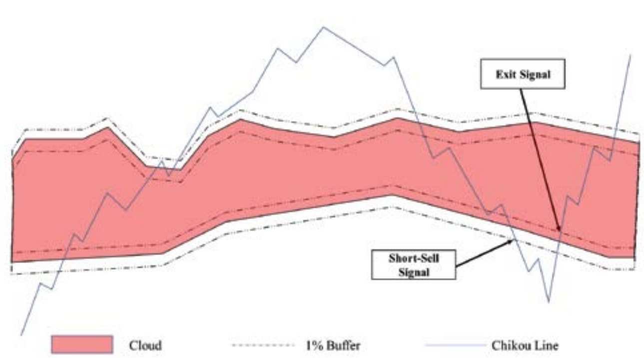


Aggressive Short-Only Strategy

The rules for this strategy are illustrated in Figure 6 and are as follows:

- Initiate a short position when the Chikou line crosses the bottom of the cloud from above.
- Close the short position when the Chikou line crosses the bottom of the cloud.

Figure 6. Illustration of Aggressive Short-Only Strategy



Evaluation of Trading Strategies

The Information Ratio (IR) was calculated to determine the profitability of our trading strategies against a benchmark. The benchmark for the conservative and aggressive long-only strategies was a long position in the stock throughout the period, and the benchmark for the conservative and aggressive short-only strategies was a short position in the stock throughout the period. This method was to attempt to quantify the additional value generated from our long-only/short-only trading strategy and to provide a proxy that could be used for an ordinal ranking of the different trading strategies. The IR was calculated over the entier period and based on a tracking error that was calculated based on monthly returns.

The calculation for the Information Ratio is as follows:

$$IR = (R_p - R_i) / \sigma p\text{-}i$$

where Rp is the return of our trading strategy portfolio, Ri is the return of the individual stock and σp-i is standard deviation of the difference between returns of the trading strategy portfolio and the returns of the individul stock.

Key Results

Overview of Results

Table 1. Overview of Trading Strategy Results

Long-Only Strategies	Conservative		Aggressive	
	US	Japan	US	Japan
Mean return (annualized)	23%	22%	11%	12%
Median return (annualized)	9%	10%	5%	5%
Median highest return	96%	107%	57%	85%
Median largest loss	-4%	-5%	-6%	-6%
Median number of trades	17	19	36	35
Median days per trade	130	105	52	46
Median information ratio	6.64	6.40	1.26	1.64

Short-Only Strategies	Conservative		Aggressive	
	US	Japan	US	Japan
Mean return (annualized)	20%	20%	13%	12%
Median return (annualized)	5%	8%	2%	3%
Median highest return	91%	112%	84%	107%
Median largest loss	-6%	-7%	-8%	-9%
Median number of trades	17	18	26	29
Median days per trade	77	95	42	52
Median information ratio	6.48	6.33	6.09	5.96

The simulation suggests that cloud charts are indeed successful at adding value and can be used to construct trading strategies that outperform simple long-only or short-only strategies.

As can be seen from Table 1, the median holding period for the conservative long-only strategy is around three to four months, whereas the median holding period for the aggressive long-only strategy is around one to two months. This is similar on the short-only side, where the median holding period for the conservative short-only strategy is two to three months, while for the aggressive short-only strategy, it is around one to two months. The number of trades generated is also significantly less for the conservative strategy compared to the aggressive strategy, with the conservative strategies generating around one to two trades annually and the aggressive strategy generating on average around three to four annual trades per stock.

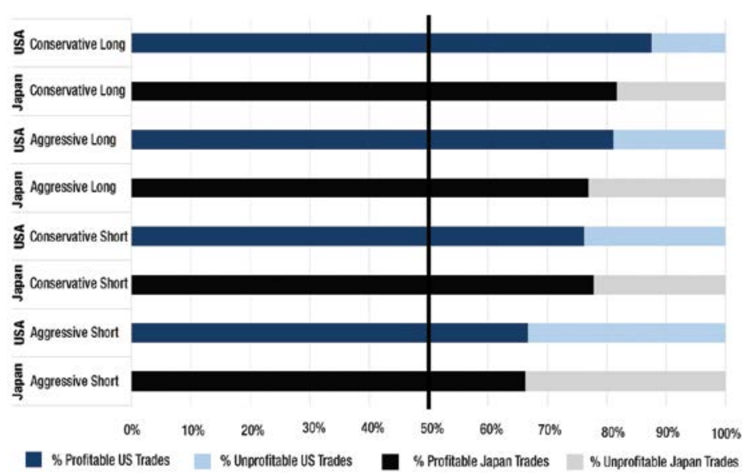
This is in line with the expectation that the conservative strategy should trade less frequently than the aggressive strategy and capture longer-term trends. It is also worth noting that the conservative strategies performed better than the aggressive strategies on both an absolute return basis as well as on a relative basis, as can be seen from the higher IRs across all markets. This suggests that the cloud charts are more effective at generating signals to capture medium-term trends.

Secondly, the strategies all exhibit a positive skew with a much smaller left tail, as can be inferred from the high maximum return and positive median return compared to the much smaller maximum loss for all of the strategies for the median stock in each market. This is consistent with the type of returns we would expect from trend-following strategies, an idea that is explored further in Section 4.4 of this paper.

Performance Comparison by Geography

From Figure 7, we can see that the cloud charts tend to generate profitable signals on both the long and short side across the two different markets. The long-only strategies tend to be more successful at generating profitable signals than the short-only strategies, and the conservative strategies tend to be more successful than the aggressive strategies. However, when we evaluate the performance across geographies, it appears to be broadly similar, with no clear advantage when the strategy is applied in either geography.

Figure 7. Median Percentage of Profitable Trades for Different Trading Strategies



This is consistent when we compare the IRs as well, as can be seen from Figures 8 through 11. These charts plot the distribution of IRs across all the stocks traded for the entire time period. Between the two geographies, there does not seem to be a clear winner, with the signals for the conservative long-only signals performing better when applied in the U.S. market, while the aggressive long-only signals performed better when applied in Japan.

Figure 8. Relative Frequency of Information Ratios for Conservative Long-Only Strategies

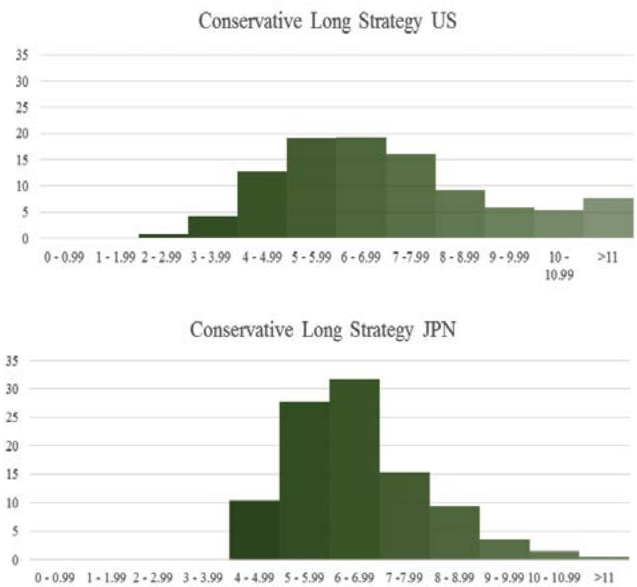


Figure 10. Relative Frequency of Information Ratios for Conservative Short-Only Strategies

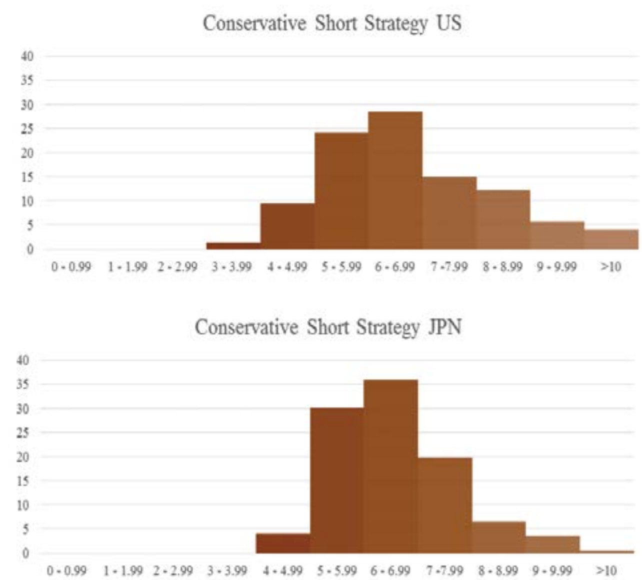


Figure 9. Relative Frequency of Information Ratios for Aggressive Long-Only Strategies

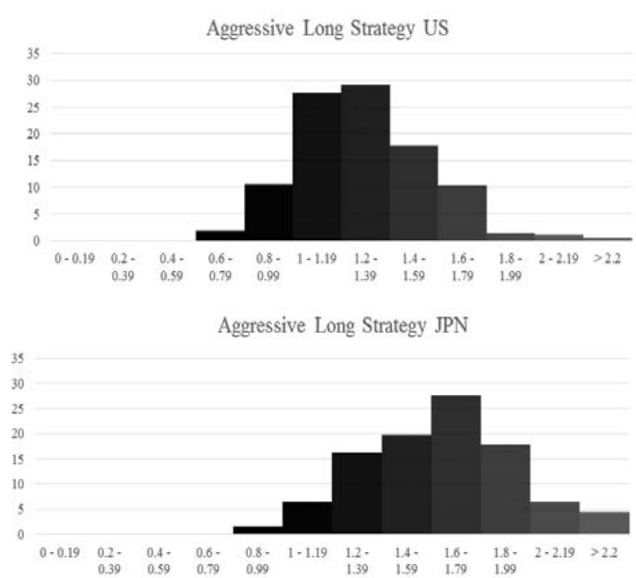


Figure 11. Relative Frequency of Information Ratios for Aggressive Short-Only Strategies

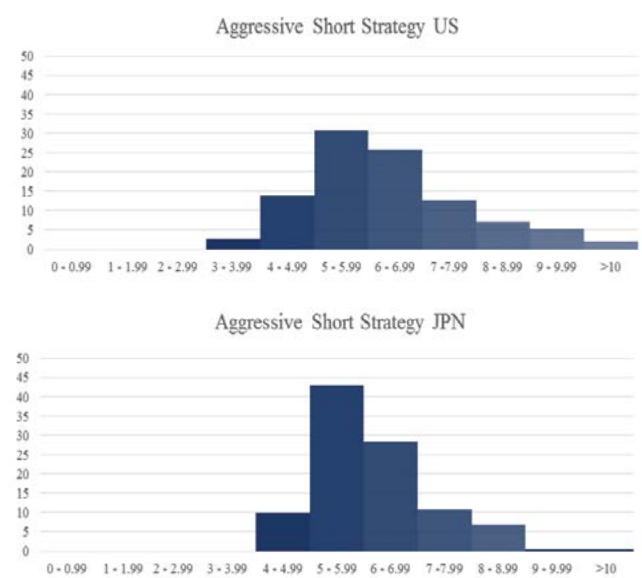


Figure 12. Performance of Trading Strategies by Year in the U.S. and Japan

From Figure 12, we can see that the majority of stocks generated positive excess returns across all the time periods in both geographies. From the chart on median excess return, we can see that the strongest returns in the United States were generated in 2008 and 2009. This is largely due to the long-only positions being cut once the crisis hit, while the short-only positions benefited from being short the stock. This is consistent with the concept of Crisis Alpha often associated with managed futures strategies, which are often based on trend-following models as well.

This is similar for the performance in Japan, with strong excess returns being generated in years with large price movements in the overall equity market and the range bound environments being associated with lower excess returns.

Possible Explanation for Outperformance

One of the key differences between the Ichimoku clouds and standard moving averages is that it averages the highest daily high and lowest daily low to construct the clouds, whereas moving averages incorporate all the prices from each day. Therefore, if there is a new high/low on that day compared to the past nine-day period, then the cloud will react more quickly than moving averages, as that new high/low price is weighted more in the cloud method, capturing important price changes faster. This also means that the clouds are not responsive to the prices that are not higher/lower than the highest/lowest price used to construct the cloud. Only the Chinkou line would respond to those weaker changes, not the clouds, making the Ichimoku method more reactive to breakouts than a standard moving average, while smoothing smaller changes compared to a system of moving averages.

Using the Ichimoku cloud charts is a way of constructing a trend-following strategy, which essentially involves buying the stocks that have been performing well in the past months and selling them as the trend begins to fade (and doing the opposite on the short-selling side). The cloud chart strategy prevents large losses by closing a signal after a stock has been performing poorly for a period of time and by not initiating a position before a trend is clearly established. The other aspect of this similarity is that a strategy based on the cloud charts allows for gains to accrue if the stock has been performing well over a long period of time by not closing the position unless the performance of the stock drops (i.e., the Chikou line crosses the cloud). However, once the trend turns against the position, the clouds and the Chikou line begin to converge, and the position is quickly closed, thus limiting losses. Therefore, large losses are prevented, but large gains are allowed to accrue over time. This natural stop-loss is consistent with our results that show that the simulated returns are positively skewed and have a large right tail but a markedly smaller left tail.

Key Limitations

There are two key methodological limitations that need to be kept in mind when evaluating the absolute performance results from the strategy. First, we have not included transaction costs in the trading strategy simulation, a factor that would have reduced the outperformance when compared to the low-turnover buy and hold or short and hold strategy. However, as the strategies primarily capture trends over a few months, the turnover each year is fairly low. Hence we would contend that the inclusion of transaction costs would lower the absolute outperformance of each strategy, but the overall conclusion that the strategies can result in outperformance would remain unchanged.

Secondly, we have not included short-selling costs or taken into account short-selling constraints in our simulation, and this could be a possible reason for the strong performance of the short-only strategies. However, we believe that while the absolute returns might be higher than what can be achieved in practice after those constraints are incorporated, it still highlights to an extent the ability of the charts to capture downtrends successfully. We believe this is still useful information for a practitioner in spite of the possible short-selling constraints and costs that might prevent one from fully extracting the value of such information.

When interpreting and evaluating the IRs reported, it is worth keeping in mind that, while IRs are typically reported against a market-based benchmark like the whole market index, we have chosen instead to use the long-only or short-only strategy of each individual stock as its own benchmark for this study. This was an intentional choice, as it highlights the ability of the charts to generate signals for each individual stock more clearly and in a comparable manner across geographies and strategies. However, as the stock is its own benchmark, this is likely to result in a lower tracking error and hence, the absolute values of the IRs observed would be higher than what would typically be achieved (as the denominator will be lower). Therefore, we would suggest that these ratios be used mainly as a way to construct an ordinal ranking of performance of these strategies against each other and not as a measure of absolute outperformance, as is common in a portfolio performance measurement context.

Conclusion

In this study, we present evidence of the ability of Ichimoku cloud charts to generate profitable trading signals in single stocks in the United States and Japan. This effect appears to be fairly persistent, and the return profiles of such a trading strategy exhibit a positive skew with a small left tail, consistent with the characteristics of other trend-following strategies.

When we compare the performance in the United States vs the performance in Japan, we find little evidence for the tool working better in one market. The continued ability of the cloud charts to generate profitable trading signals is probably a key reason this tool has remained popular amongst technical analysts decades after these concepts were first proposed. Through this study, we have provided some empirical evidence for the characteristics of the information provided and would encourage further empirical work on the other signals that can be generated from the charts as well as ways that the cloud charts can be optimised for each market to deliver better signals.

Software

Charts for Figures 1 and 2 taken from www.ichimokutrader.com.

Stock price data was obtained from Bloomberg, and market data for Figure 12 was obtained from Yahoo Finance.

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An Examination of Co-integration of Web Search Volumes and Trading Volumes for Selected Shares Traded on the London Stock Exchange

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Abstract

This paper investigates statistical properties of Web search volume and trading volume time series in a process known as co-integration. The procedures employed in testing for co-integration aim to explain whether there is a statistically significant relationship between Web search volume and trading volume. The results of the co-integration relationship between the two time series are depicted in a technical indicator, WESTVOL. This new indicator informs market participants whether moves in search volume data can predict similar moves in trading volume for selected stocks traded on the London Stock Exchange.

The study undoubtedly contributes to current knowledge on the relationship between Web searches and trading volumes, especially with regard to technical analysis. This work serves as a good basis for further improvements in the methodology design as well as implementation of the WESTVOL indicator with statistical modelling in R code.

Introduction

Background

The advent of fast computer processing and the vast availability of financial data at the stroke of a key has allowed the co-integration of methodologies and approaches to enter the financial world. Such models are generally built on an assumption that a variable or set of variables—the independent variables—cause changes in another variable—the dependent variable. Time series are commonly analysed or programmed with statistical software R, with which large sets of data can be analysed and tested for efficiency and forecasting. These models, often called black-box models, simply follow predefined logic that has been extensively tested and validated for specific financial datasets and scenarios.

Financial models normally utilise financial or economic data as predictors, independent inputs, in their models. According to Askitas and Zimmermann (2009), the classical econometrics discipline is still needed to fully appreciate the value of Web search volumes. Therefore, my argument in this thesis is to apply Web search volumes as a reliable input to predict share-trading volume changes.

I built this discussion mainly on outstanding work by Choi and Varian (2009a, 2009b, 2011); Preis, Reith, and Stanley (2010); Da and Engelberg (2011a, 2011b, 2011c); and Bordino et al. (2012), who investigated links between Google Web search and economic indicators, such as company revenues and stock trading volumes. In the field of R programming, the work of Ssekuma (2011) on the application of co-integration methods to economic data has been my primary source of inspiration for this thesis. Finally, I will be taking all the analysis further, and based on the co-integration outcome, I will propose the technical indicator WESTVOL.

The Theoretical Basis

Time series at the highest level can be described by two key properties: non-stationarity and volatility. For a time series to be described as non-stationary, its values should not converge to a constant mean, which is also known as a trending series. Volatility, on the other hand, describes the deviations of its values around its mean. In addition, the co-integration between two series explains the type of relationship between them (i.e., diverging away or moving closer over time); normally, it is argued that this relationship holds on a long-term basis (Brooks 2008). Furthermore, the presence of a unit root, which describes characteristic roots in time series, plays a vital role in co-integration testing. Hence, it is accepted that differencing time series by a predefined lag solves this problem in an approach known as the unit root process (Ssekuma, 2011).

Testing for non-stationarity and the presence of unit roots involves regressing the Web search and stock trading volume series by a one-period lagged value utilising the Augmented Dickey-Fuller (ADF) test. Both series need to pass the ADF test to be assumed to contain a unit root, according to DeFusco et al. (2007).

Finally, co-integration of the two series is to be quantified with application of the Engle-Granger method, assuming stationarity in the linear combination of the two series. This is followed by the Philips-Ouliaris test of auto-regression by the order of one and Johansen's test of multi-vector, utilising maximum likelihood estimation.

Aims and Objectives

The aim of this paper is to examine co-integration between Web search volumes and share trading volumes for selected shares on the London Stock Exchange by application of the methodological processes outlined above. More importantly, my findings should indicate whether the co-integration gives rise to predictive attributes of Web search volumes on stock trading volumes. The proposed aims and objectives are defined below:

1. *Are the data valid time series?* To provide background information, such as normality, correlation levels and trend patterns for the two time series.
2. *Can the data be co-integrated?* To establish the methodology and processes for testing co-integration.
3. *Have the co-integration methodology and processes been effective?* To analyse and interpret the co-integration results.

4. *Can the co-integration findings be used to forecast stock trading volumes?* This is to explain whether Web searches can be used to forecast stock trading volumes and to develop an indicator to graphically display the relationship between Web search volumes and trading volumes.

Literature Review

Co-integration Models

Sir Clive William John Granger (Granger, 1969) argues that if series Y_t possesses information in its past terms that could help with prediction of some other series X_t and, furthermore, this information is not contained in other series used in the predictor, then Y_t is assumed to cause X_t. The two important attributes that describe time series and are undesirable for co-integration purposes are non-stationarity and the presence of unit root. According to Box, Jenkins, and Reinsel (2008), one needs to individually differentiate the series by an appropriate number of times (di) to achieve stationarity in series. On the other hand, Pfaff (2008) argued that the linear combination of two non-stationary vectors can exhibit stationarity, provided the series are all tied to each other by a co-integrating vector.

Moreover, the non-stationary series is claimed to possess a unit root if it exhibits at least one significant root. In other words, unit root is also present if the first differences of non-stationary data are stationary (Chatfield 2004) and can be depicted using the auto-correlation (ACF) and partial auto-correlation (PACF) correlograms at specified legs in the time series. This brings my discussion to the argument expressed by DeFusco et al. (2007) that non-stationarity in series can be found when either ACF does not drop off to zero or it is statistically distinguishable at some lags. In conclusion, Dickey and Fuller (1979) proposed a set of tests I will be utilising in this research to assist with calculating the unit root level by analysing limiting distributions of p^ and r^, given the hypothesis that |p| = 1. Where the value of |p|, according to Ssekuma (2011), is a lag number in which PACF is significant or where ACF is at a cut-off point.

Stationarity in time series, according to Pfaff (2008), is the desirable attribute in order to avoid "spurious regression" or "nonsense regression" in the co-integration results. For that reason, the Engle-Granger test aims to establish linear combinations between two I(d) variables in two-step tests for unit root and Error-Correction Model (ECM). The methodology was tested by Engle, Granger, Hylleberg, and Lee (1993) on consumption and disposable income in Japan between 1961 and 1987, and it concluded that the two series were integrated in the order of 1. A similar two-step process has also been devised by Philips-Ouliaris (Pfaff, 2008), which is based on residuals of the first-order vector auto-regression, producing a variance ratio statistic P^z *and multivariate trace statistic P*^z. Kanas (1997) utilised Philips-Ouliaris tests on co-integration between commodities exports from the UK to the US, and the real exchange rates between 1981 and 1988 concluded satisfactorily. Furthermore, the author also ran data on Johansen's model, which builds co-integrated variables directly on maximum likelihood estimation instead of relying on Ordinary Least-Squares estimation (Ssekuma, 2011), and concluded in favour of that model. It is generally accepted that Johansen's process shows its superiority in the fact that it allows for tests of "q" homogenous restrictions imposed on "r" co-integrating vectors and its ability to detect more than one co-integrating relationship (Ssekuma, 2011).

Google Search Volumes in Econometrics

Early Google Trends

Since the Internet grew in popularity in the early 21st century, adaptation of Web search browsers and dependence on the search tools has grown rapidly (Fallows, 2004, cited in Liu et al., 2008). One of the earliest and most prominent studies of Web searches was undertaken by Cooper et al. (2005), who correlated search volumes against cancer evidence and concluded that the Internet can offer an innovative insight into health information-seeking behaviour. Along a similar strand, Ginsberg et al. (2012) praised the Web search engine as a broad-reaching influenza monitoring system after regressing Web searches on influenza breakouts.

In contrast, Palmer (2008) questions the predictive power of Google trends, and this was supported by Lui, Panagiotis, and Mustafaraj (2011), who concluded weak correlation of Google search data and the likelihood of winning the 2008 and 2010 elections in the United States.

Evidence in Econometrics

Research papers from Choi and Varian (2009a, 2009b, 2011) offer the best starting point for econometric analysis of Web searches with R code utilisation. The authors have undertaken co-integration using auto regressive models to predict house prices, concluding that a percentage point increase in Web search volume correlated with additional 67,220 house sales (Choi and Varian, 2009a). Furthermore, unemployment and Gross Domestic Product in the United States (Choi and Varian, 2009b, 2011; Schmidt and Vosen, 2009), Germany (Askitas and Zimmermann, 2009), and Italy (D'Amuri, 2009) were regressed with Web searches; however, the quarterly data frame posed challenges due to its short time span (Schmidt and Vosen, 2009). More importantly, the benefit of Web searches is greatly appraised in times of economic recession (Askitas and Zimmermann, 2009) and higher economic uncertainty (Castle, Fawcett, and Hendry, 2009).

On a microeconomic scale, Kulkarni, Kannan, and Moe (2012) proposed that Google searches are a valid predictor of company sales and that the very same Web search data explains current-quarter company revenues (Da, Engelberg, and Gao, 2011b).

Stock Market

Positive correlation between a Web search and stock ticker codes was conducted by Joseph, Babajide, and Zhang (2011), providing a proxy of investor sentiment toward a stock. Similarly, Bordino et al. (2012) correlated a Web search for stock tickers with stock volumes utilising only Granger statistical tests; however, they concluded that a Web search leads to stock volume in the following days.

In contrast, since an average user is less likely to browse for companies by means of a ticker-code search (Da, Engelberg, and Gao, 2011a), some analysts turned to co-integrating full company name-related searches with stock returns (Bank, Larch, and Peter, 2011), providing evidence of a positive short-run relationship between changes in these two variables. Similarly, Preis, Reith, and Stanley (2010) suggested that a search for a company name and its correlation with trading volume can undoubtedly assist with predicting financial bubbles.

Statistical Software R

The most prominent paper on the application of R code in econometrics, produced by Ssekuma (2011), investigates three co-integration methods: the Engle-Granger, Philips-Ouliaris, and Johansen tests. The author's analysis includes R code application, theoretical comparison of different tests as well as co-integration analysis of consumption, income and wealth series for the United Kingdom between 1966 and 1991, Australia's Economic Indicators between 1999 and 2009, and the United Kingdom's Purchasing Parity. The author favoured the Engle-Granger test due to its ease of implementation; however, Johansen's test can claim superiority due to its vector co-integration techniques allowing tests for more than one co-integrating relationship.

In contrast, Kolassa and Hyndman (2010) argued R's steep learning curve as its drawback as well as a lack of a Graphical User Interface (GUI), which increases the chances of typing errors (Fox, 2005). On the other hand, GUI packages, such as SAS, SPSS, and Excel, were found to lack accuracy and incur financial cost from purchasing a license (Keeling and Pavur, 2005).

Methodology

Objectives and Scope of the Study

Aim and Objectives

The aim of this research will be achieved with application of co-integration models for Web search volumes and stock trading volumes (Choi and Varian, 2009a, 2009b, 2011; Da and Engelberg, 2011a, 2011b, 2011c). The desired outcome is to forecast the likelihood of increased trading activity, as measured by trading volumes (Bordino et al., 2012), through application of R statistical models (Ssekuma, 2011).

The intention is to perform the following statistical calculations to achieve the objectives.

1. *Diagnostic Test:* To provide background information, including standard deviation, auto-correlation, normality, and trend patterns for the two time series.
2. *Test for Unit Root*: To establish the methodology and processes for testing co-integration by utilising Augmented Dickey-Fuller and Philips-Perron tests.
3. *Hypothesis 1 Test: Co-integration*
   To explain the extent to which the co-integration methodology and processes have been effective with application of Engle-Granger, Philips-Ouliaris, and Johansen tests.
4. *Hypothesis 2 Test: Forecasting*
   To explain whether Web searches can be used to forecast stock trading volumes and to develop WESTVOL indicators to graphically display the relationship between Web search volumes and trading volumes.

Scope

To achieve the objectives, the delimitations and established boundaries need to be defined (Sevilla et al., 2007). By undertaking this research, current knowledge will be extended in the areas described below.

1. Analysis of Web searches at ticker-code level, thereby capturing market participants' interest in the stock.
2. Building upon work on co-integration of Web search volumes and trading volumes by utilising multiple co-integration tests to reaffirm the results.
3. Attempting to create technical indicators to graphically describe the relationship between a Web search and trading volume so that Web search activity could alert market participants of increasing trading volume.
4. This investigation will utilise current knowledge in R coding, enabling like-minded individuals to easily pick up the coding and run/extend this work in their own applications.

Formulation of Hypotheses

When working with hypothesis testing, one needs to be aware of Type 1 and Type 2 errors (Coldwell and Herbst, 2004). Type 1 error is identified when the H_0 hypothesis is wrongly rejected, making H_1 wrongly accepted. In contrast, Type 2 error is characterised by incorrect acceptance of the H_0 hypothesis, which results in the H_1 hypothesis being wrongly rejected.

The two hypotheses proposed for investigation in this research are presented below.

1. *Hypothesis 1: Co-integration of Web search volumes and stock trading volumes*

   H_0: The level of co-integration of Web search volumes and stock trading volumes for selected stocks traded on LSE is not significant.

   H_1: The level of co-integration of Web search volumes and stock trading volumes for selected stocks traded on LSE is significant.

2. *Hypothesis 2: Forecasting the power of Web search volumes on stock trading volumes, under one condition that Hypothesis 1 H_0 is rejected*

   H_0: The forecasting power of Web search volumes on stock trading volumes for selected stocks traded on LSE is not significant.

   H_1: The forecasting power of Web search volumes on stock trading volumes for selected stocks traded on LSE is significant.

Data Collection

Secondary data is used for this research, as it has already been collected by Google Trends and Google Finance (Google, 2012a, 2012b), and its instant and wide availability makes it an extremely cost-effective source. However, its accuracy or relevance could be questioned by proponents of primary data sources, which are collected specifically and afresh for particular research (Kothari, 2006). I looked specifically at the reliability, suitability, and adequacy characteristics of the secondary data. The fact that these datasets originate from Google repositories would make one comfortable that its reliability aspects, such as collection methods, sources, and accuracy, would be adequate for this research. Regarding suitability and adequacy, Google is the only search engine provider that discloses search volumes and trading volumes with great granularity, allowing for detailed analysis; hence, no equivalent sources were available at the time of writing this research.

Both series are collected for specific keywords searched on Google Trends and Google Finance, as depicted in Table 1.

Table 1. Keyword Selection

Company	Keyword Used on Google Trends and Google Finance
HSBC Holdings	HSBA
SABMiller	SAB
Vodafone Group	VOD
Glencore Xstrata	GLEN
Prudential	PRU

Data Analysis

Data Introduction

Five stocks traded on the LSE were chosen for this research, as presented in Table 2. The choice was based primarily on market cap of the stock as well as availability of Web search volumes. Therefore, most large capitalisation stocks—the top quartile of FTSE 100—were the best candidates for this research, regardless of their sector classification. Companies in all the tables in this research are presented in descending order, with the largest market cap at the top.

Table 2. Company Selection and Descriptions

Company	Ticker	Market Cap	Sector
HSBC Holdings	HSBA	115bn	Financials
SABMiller	SAB	54bn	Non-Cyclical Consumer
Vodafone Group	VOD	50bn	Telecommunications Services
Glencore Xstrata	GLEN	43bn	Energy
Prudential	PRU	34bn	Financials

The time span of data available for the research is presented in Table 3, as it varies for each company. Full datasets are available in Appendix A.

Table 3. Company Data Ranges

Company	Date Start	Date End	Number of Data Items
HSBA	04/05/2008	22/06/2014	321
SAB	07/01/2007	22/06/2014	390
VOD	03/05/2009	22/06/2014	269
GLEN	02/01/2005	22/06/2014	495
PRU	02/01/2005	22/06/2014	495

The trading volume data has been rebased using Formula 1, whereas the Web search data has already been rebased by Google (Google, 2012b).

Formula 1. Rebased 100

$$\text{Rebased } 100 = \frac{\text{Data Value}}{\text{Base Data Value}} \times 100$$

Table 4 displays a summary of the data analysed in this study.

Table 4. Data Summary

Company	Variable	Min.	1st Qu.	Median	Mean	Mode	3rd Qu.	Max.
HSBA	Search	14.00	32.00	38.00	41.43	38.00	50.00	100.00
	Volume	3.00	10.00	14.00	16.37	10.00	19.00	100.00
SAB	Search	17.00	32.00	38.00	39.39	38.00	45.75	100.00
	Volume	2.00	10.00	13.00	18.28	10.00	25.00	100.00
VOD	Search	19.00	35.00	42.00	73.76	37/39 /46	51.00	100.00
	Volume	1.00	7.00	10.00	10.00	10.00	10.00	24.00
GLEN	Search	29.00	46.00	51.00	51.45	50.00	56.00	100.00
	Volume	1.00	3.00	4.00	5.35	3.00	7.00	34.00
PRU	Search	7.00	12.00	14.00	14.98	12.00	17.00	100.00
	Volume	1.00	5.00	11.00	13.17	4.00	19.00	79.00

Data Formatting

The formatting operations presented in Table 5 were undertaken on data in this study.

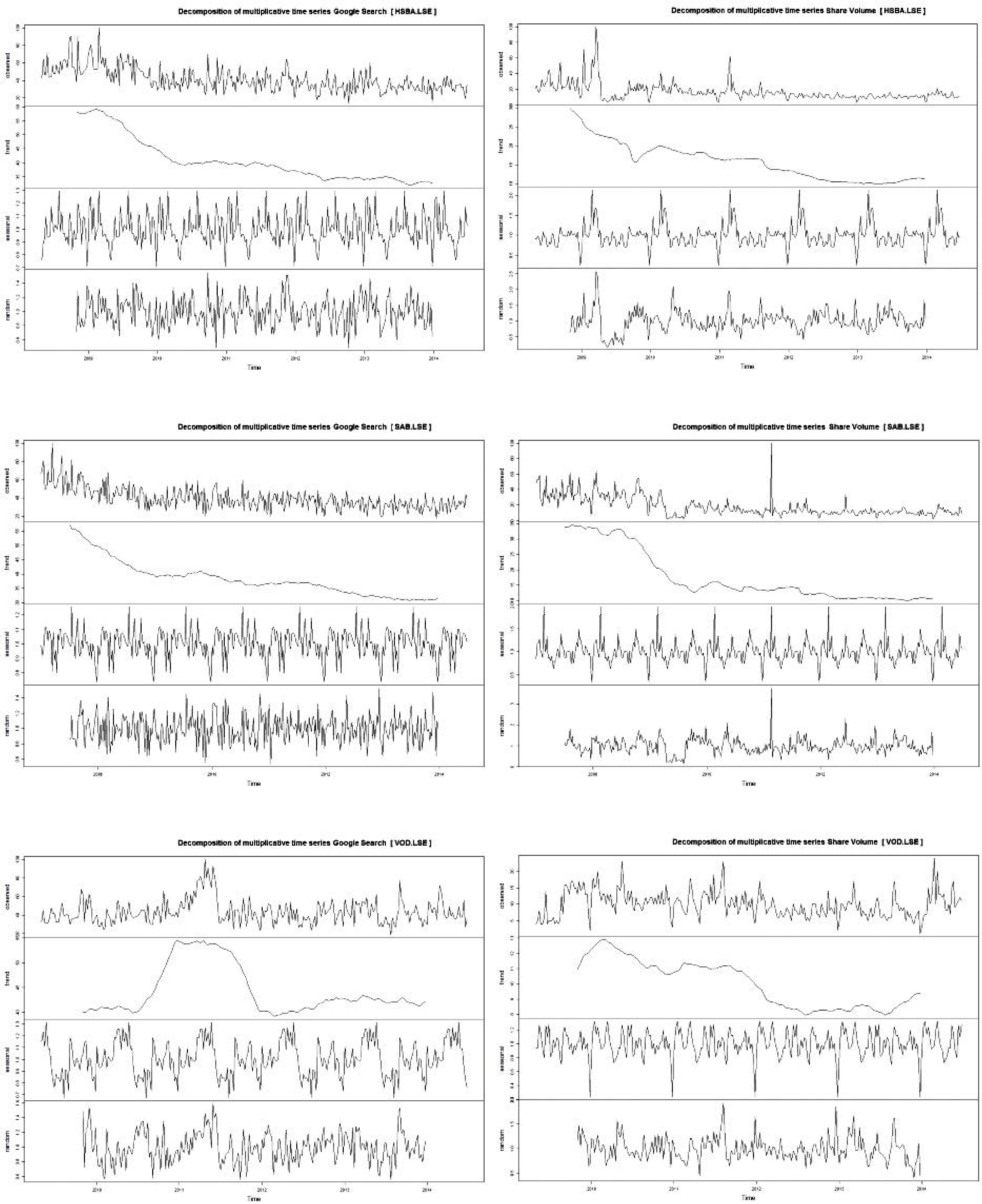
Table 5. Data Formatting

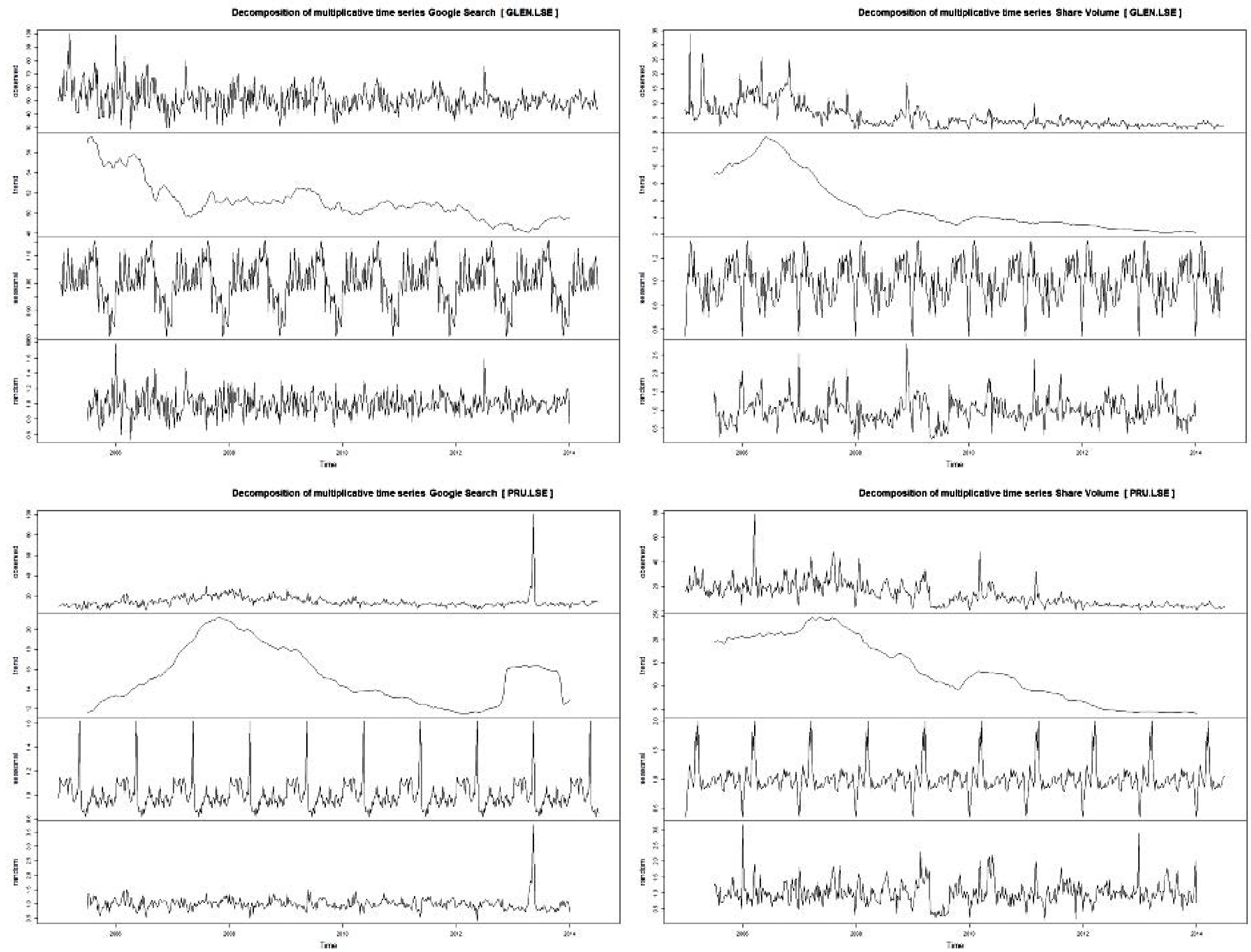
Data Type	Date	Volume (Rebased 100)	Search (Rebased 100)
Format	yyyy-mm-dd	00	00

Time Series Conversions

The Web search and trading volume data were converted to a time series (ts) object in the R environment so that these could be easily used as input parameters for various methods used during testing. Moreover, series were also decomposed into trend, seasonal, and random components for ease of usage in calculations. Figure 1 depicts the decomposed series.

Figure 1. Decomposed Trend, Seasonal and Random Components





Final Data Plots

To aid visual inspection of the data series, unchanged as well as detrended plots are presented in Figure 2, followed by Figure 3, which presents correlation plots and their strength.

Methods

The Web searches and stock trading volume data are combined into one file consisting of date, volume, and volume rebased 100 and search rebased 100 columns. Rebasing is achieved relative to the highest volume/search figure in the series and set at 100. Five Comma Delimited (CSV) files are created and passed to the R environment, examples of which are available in Appendix A.

Tests for co-integration are computed in R code, starting with the application of formatting to the date and time series, using Date(), ts(), and decompose() functions respectively. This is followed by a set of diagnostic tests, such as sd(), acf(), pacf(), shapiro.test(), and unit root tests, such as ur.df(), diff(), and ur.pp(). Finally, co-integration is tested using lm(), ar(), ur.df(), ca.po(), and ca.jo() functions, followed by indicator building with ggplot(). The source code for this process is attached in Appendix B.

Results

Diagnostic Results

Standard Deviation

DeFusco et al. (2007) suggest a three-step process, as presented in Table 6, to calculate standard deviation (SD) to measure dispersion of values around their arithmetic mean.

Table 6. Three-step Standard Deviation Calculation Process

Step	Process
Step (1)	SD of the main Web search volumes and trading volumes.
Step (2)	SD of these sets after removing trend component.
Step (3)	SD of these sets after seasonal adjustment.

Table 7 depicts results for the processes in Table 6, indicating that the SD decreases once further steps are implemented. Ultimately, a very low SD is found for all stocks analysed in this report.

Figure 2. Actual and Trend Data

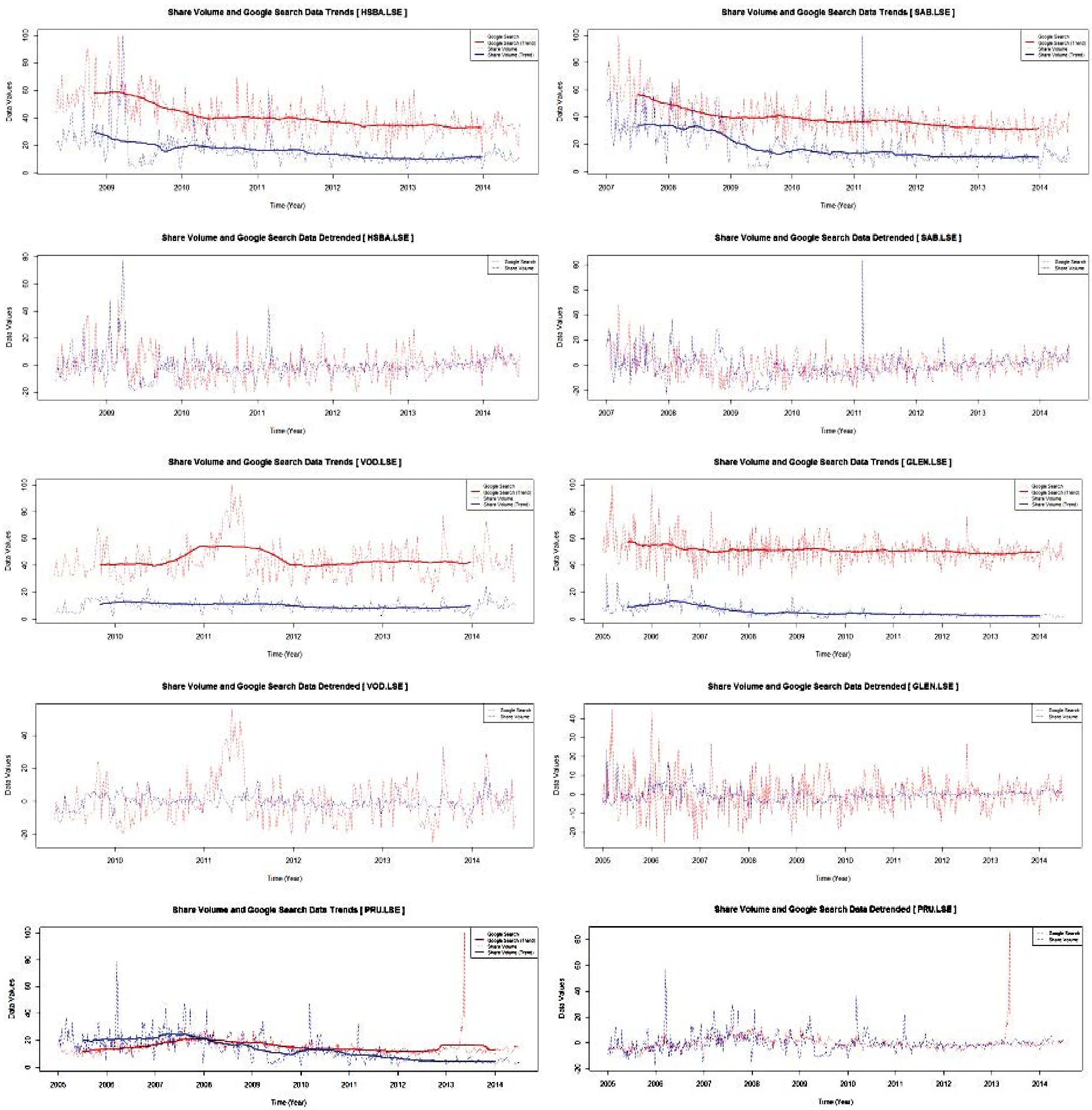
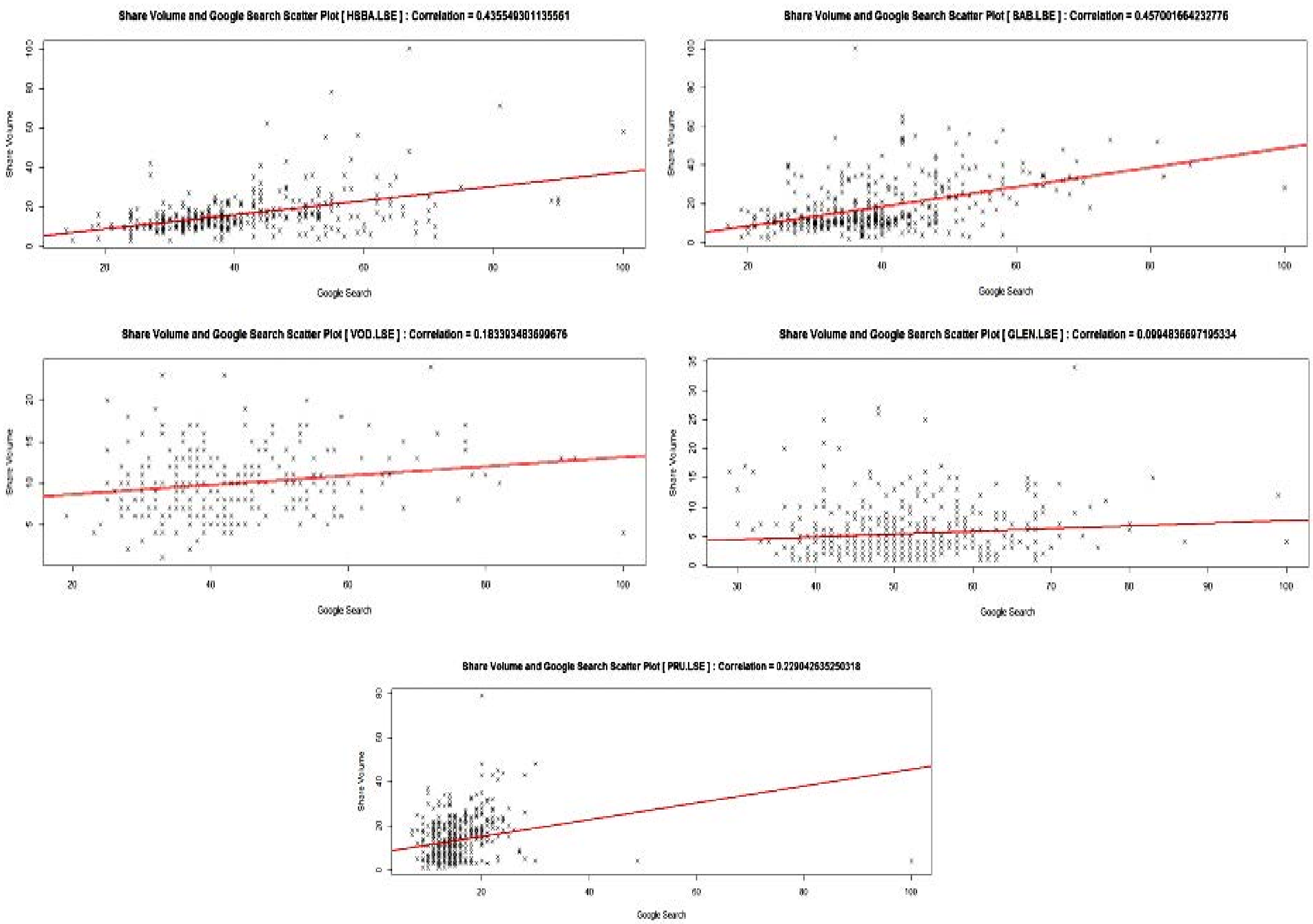


Table 7. Standard Deviation Analysis

Company	Variable	(1) Main Sets	(2) Subtracted Trend	(3) Seasonal Adj.
HSBA	Search	12.94403	10.12669	0.2070298
	Volume	11.17152	10.01889	0.3477033
SAB	Search	10.00471	7.986104	0.1822886
	Volume	12.41015	8.720431	0.3762618
VOD	Search	13.70343	12.22572	0.2118643
	Volume	3.658214	3.202289	0.2469814
GLEN	Search	8.94841	8.780841	0.148403
	Volume	4.070417	2.426024	0.3679264
PRU	Search	5.953413	5.135724	0.2275703
	Volume	9.618534	6.57254	0.3707912

Figure 3. Scatter Plots



Auto-correlation

The auto-correlation tests were performed with ACF and PACF correlograms depicting the mean and variance because Cowpertwait and Metcalfe (2009) suggest that these summarise the two key distributional components of central location and spread. For visual inspection of ACF and PACF plots, please refer to Figure 4. The lag order was calculated empirically from Akaike Information Criterion (AIC) (Pfaff, 2008), which are presented in Table 8, and applied in the unit root and co-integration tests.

Table 8. Akaike Information Criterion

Company	Series	Lag Order
HSBA	Search	6
	Volume	9
SAB	Search	9
	Volume	7
VOD	Search	3
	Volume	2
GLEN	Search	5
	Volume	11
PRU	Search	3
	Volume	11

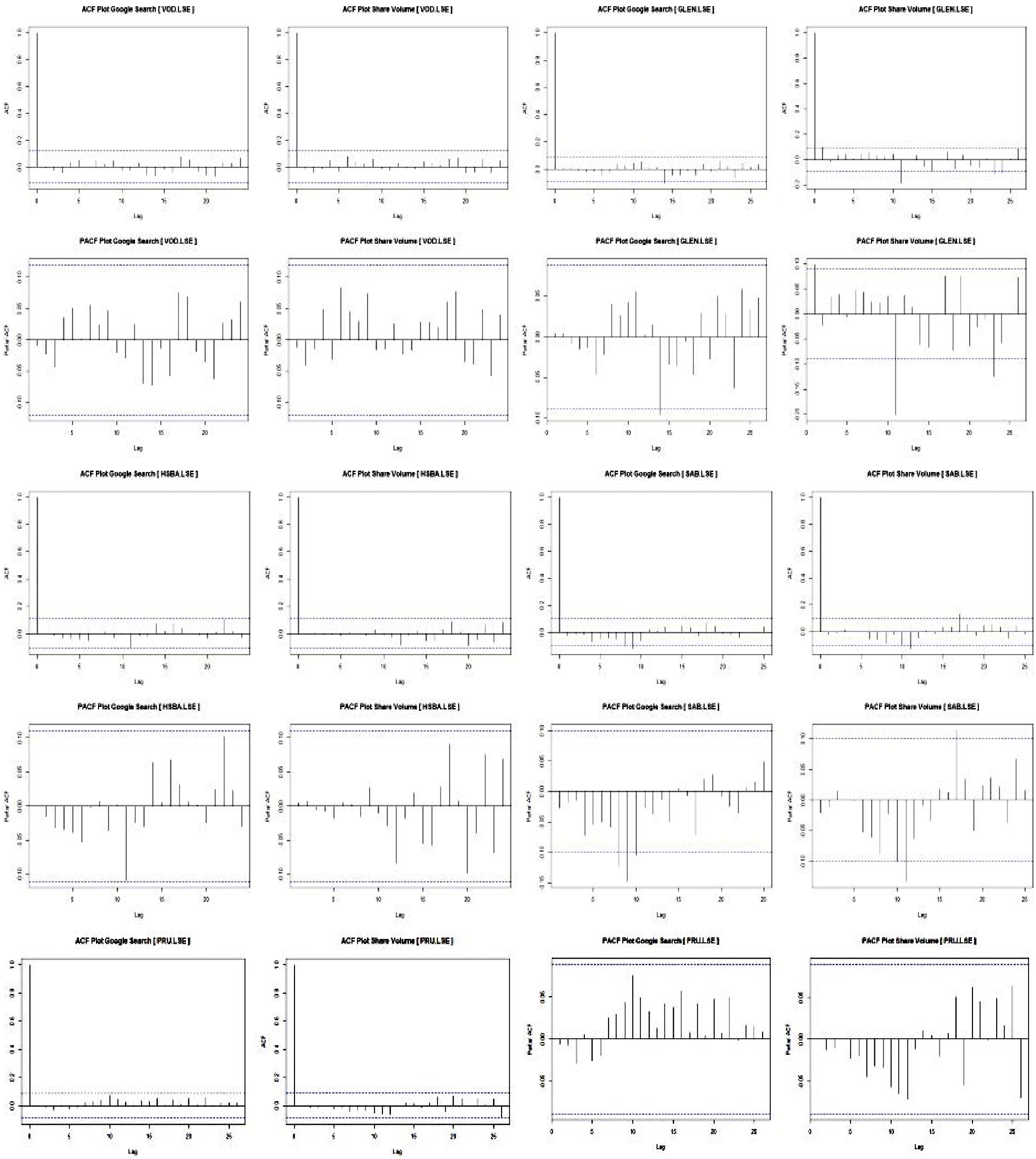
Test for Normality

In the Shapiro-Wilk test for normality, the author reveals if arguments in the series are well modelled by a normal distribution (Ssekuma, 2011). Table 9 shows that all p-values fall between 5 to 16 decimal places, which are well below the cut-off threshold of 0.05 alpha levels.

Table 9. Shapiro-Wilk Test Results

Company	Variable	Shapiro-Wilk	p-value
HSBA	Search	0.9409	$5.04e^{-10}$
	Volume	0.7266	$2.2e^{-16}$
SAB	Search	0.938	$1.11e^{-11}$
	Volume	0.8344	$2.2e^{-16}$
VOD	Search	0.9187	$6.195e^{-11}$
	Volume	0.9707	$2.571e^{-5}$
GLEN	Search	0.9522	$1.462e^{-11}$
	Volume	0.7737	$2.2e^{-16}$
PRU	Search	0.6144	$2.2e^{-16}$
	Volume	0.8823	$2.2e^{-16}$

Figure 4. ACF and PACF Plots for Original Datasets



Test for Unit Root

Augmented Dickey-Fuller

Trend and Drift Terms

The $\tau3$, ø2 and ø3 test statistics returned from this model indicate significance levels for the unit root. Table 10 presents the test statistics as well as critical levels. This test reveals the presence of at least one unit root by testing for the presence of integration of order one I(1) in series. All stocks, except SAB Web search and GLEN trading volume series, fall below the 1% significance level on the $\tau3$, ø2 and ø3 test statistics.

Similarly, testing the drift term with application of the same lag argument produces the results shown in Table 11. The $\tau2$ *statistic ranges from -1.7466 (GLEN) to -7.231 (GLEN), and the ø1 statistic scored between 1.6059 (GLEN) and 26.153 (GLEN).*

Table 10. Augmented Dickey-Fuller Trend Term Results

Company	Test Statistic	τ_3			$ø_2$			$ø_3$		
	Thresholds	1%	5%	10%	1%	5%	10%	1%	5%	10%
	Critical Values	-3.98	-3.42	-3.13	6.15	4.71	4.05	8.34	6.30	5.36
HSBA	Search	-4.607			7.1306			10.6164		
	Volume	-4.9134			8.0872			12.0826		
SAB	Search	-3.6771			4.9447			7.1798		
	Volume	-4.5026			6.8555			10.1886		
VOD	Search	-4.3177			6.2536			9.38		
	Volume	-6.2407			12.9916			19.4785		
GLEN	Search	-7.8707			20.6568			30.9756		
	Volume	-3.054			3.1725			4.6772		
PRU	Search	-6.625			14.6357			21.9522		
	Volume	-5.0872			8.7446			12.9429		

Table 11. Augmented Dickey-Fuller Drift Term Results

Company	Test Statistic	τ_2			$ø_1$		
	Thresholds	1%	5%	10%	1%	5%	10%
	Critical Values	-3.44	-2.87	-2.57	6.47	4.61	3.79
HSBA	Search	-2.6035			3.4652		
	Volume	-3.5995			6.5246		
SAB	Search	-2.7365			3.9778		
	Volume	-3.0051			4.6073		
VOD	Search	-4.3179			9.3226		
	Volume	-5.9973			17.9928		
GLEN	Search	-7.231			26.153		
	Volume	-1.7466			1.6059		
PRU	Search	-6.542			21.4004		
	Volume	-2.5262			3.3584		

Second Order of Integration

The order of integration test, also known as I(2), or second order, is undertaken by differencing the series in the ADF model. The results are illustrated in Table 12.

Table 12. Augmented Dickey-Fuller Second Order of Integration Results

Company	Test Statistic	τ_1		
	Thresholds	1%	5%	10%
	Critical Values	-2.58	-1.95	-1.62
HSBA	Search	-10.4912		
	Volume	-7.869		
SAB	Search	-10.4501		
	Volume	-9.8861		
VOD	Search	-11.6284		
	Volume	-13.7892		
GLEN	Search	-13.3189		
	Volume	-9.263		
PRU	Search	-15.4335		
	Volume	-9.9297		

All results yield extremely low values for the $\tau1$ statistic, from -7.869 (HSBA) to -15.4335 (PRU), which are all well below the 1% threshold.

Philips-Perron

Trend and No-Trend Models

The $Z(\tau\alpha)$ statistic produced in this test is presented in Table 13, in which values are tested against the ADF threshold figures from previous tests. It appears all values in this test fall below the 1% threshold of -3.98668.

Furthermore, removing the trend component produces the test statistic $Z(\tau\mu)$ presented in Table 14. Similar to the results for the trend model, all $Z(\tau\mu)$ values fall well below the 1% threshold level of -3.44989.

Table 13. Philips-Perron Trend Model Results

Company	Test Statistic	$Z(\tau_\alpha)$		
	Thresholds	1%	5%	10%
	Critical Values	-3.98668	-3.42362	-3.13448
HSBA	Search	-16.5278		
	Volume	-8.8357		
SAB	Search	-18.2248		
	Volume	-13.9681		
VOD	Search	-10.0367		
	Volume	-10.1058		
GLEN	Search	-18.2755		
	Volume	-14.4955		
PRU	Search	-14.1554		
	Volume	-13.5365		

Table 14. Philips-Perron No-Trend Model Results

Company	Test Statistic	$Z(\tau_\mu)$		
	Thresholds	1%	5%	10%
	Critical Values	-3.44989	-2.86954	-2.57101
HSBA	Search	-14.3573		
	Volume	-8.3938		
SAB	Search	-15.3008		
	Volume	-10.7307		
VOD	Search	-10.0528		
	Volume	-10.2186		
GLEN	Search	-18.4741		
	Volume	-10.4119		
PRU	Search	-14.1412		
	Volume	-10.1748		

Series Differencing

Similar to the second step of the ADF test, this method also differences the series in order to perform tests. The statistical value $Z(\tau\beta)$ is shown in Table 15.

Table 15. Philips-Perron Series Differencing Results

Company	Test Statistic	$Z(\tau_\beta)$		
	Thresholds	1%	5%	10%
	Critical Values	-3.98674	-3.42365	-3.13449
HSBA	Search	-68.6131		
	Volume	-33.0667		
SAB	Search	-78.0868		
	Volume	-59.2104		
VOD	Search	-36.0049		
	Volume	-39.2687		
GLEN	Search	-72.1975		
	Volume	-54.1337		
PRU	Search	-55.136		
	Volume	-52.3677		

Similar to the former ADF test, the series differencing values fall well below the 1% threshold for all series.

Hypothesis 1 Test: Co-integration

Engle-Granger

Ordinary Least-Squares Estimation

The regression of Web searches on trading volumes and vice versa provides a value for the strength of this test, expressed as the R-squared value presented in Table 16.

Furthermore, the residuals of these values are also tested for co-integration, and the results are shown in Table 17. Values for the R-squared statistic range from relatively strong readings of 0.2068 (SAB) and 0.1872 (HSBA) to rather weak results in the cases of PRU (0.05054), VOD (0.03001), and GLEN (0.007889). It appears that most of the series, except for the GLEN (-1.8104) and PRU (-2.7336) trading volumes, fall below the 1% threshold, which is similar to the ADF test results presented earlier.

Table 16. Engle-Granger Ordinary Least-Squares Estimation Regression Test Results

Company	Regression	p-value	R-squared
HSBA	Search ~ Volume	$2.715e^{-16}$	0.1872
	Volume ~ Search	$2.715e^{-16}$	0.1872
SAB	Search ~ Volume	$2.2e^{-16}$	0.2068
	Volume ~ Search	$2.2e^{-16}$	0.2068
VOD	Search ~ Volume	0.002532	0.03001
	Volume ~ Search	0.002532	0.03001
GLEN	Search ~ Volume	0.02688	0.007889
	Volume ~ Search	0.02688	0.007889
PRU	Search ~ Volume	$2.582e^{-7}$	0.05054
	Volume ~ Search	$2.582e^{-7}$	0.05054

Table 17. Engle-Granger OLS Co-integration Test Results

Company	Test Statistic	τ_1		
	Thresholds	1%	5%	10%
	Critical Values	-2.58	-1.95	-1.62
HSBA	Search	-3.753		
	Volume	-7.7088		
SAB	Search	-3.3902		
	Volume	-3.6815		
VOD	Search	-4.2662		
	Volume	-6.0043		
GLEN	Search	-7.6439		
	Volume	-1.8104		
PRU	Search	-6.9262		
	Volume	-2.7336		

Error-Correction Model

This step tests for Granger-causation in the direction from Web search to trading volume. The first difference of the series will be tested and then further regressed in order to determine the direction of the relationship. Results for this test are presented in Table 18 below.

Table 18. Granger-Causation Test Results

Company	Error-Correction Term Estimate
HSBA	-0.005469
SAB	-0.07026
VOD	0.01443
GLEN	0.0009195
PRU	0.01025

Only two stocks, HSBA and SAB, record negative term estimates of -0.005469 and -0.07026, respectively.

Philips-Ouliaris

Variance Ratio

The (P^u) statistic for the variance ratio test is presented in Table 19. All of the analysed stocks record extremely large results that are significantly below the 1% cut-off level.

Table 19. Philips-Ouliaris Variance Ratio Test Result

Company	P^u		
	1%	5%	10%
	48.0021	33.713	27.8536
HSBA	348.6176		
SAB	348.9582		
VOD	210.0732		
GLEN	569.2699		
PRU	375.838		

Multivariate Ratio

The (P^z) statistic for the multivariate ratio test is presented in Table 20. Very similar to the former (P^u) test, it appears that all of the analysed stocks record extremely large results that are, yet again, significantly below the 1% cut-off level.

Table 20. Philips-Ouliaris Multivariate Ratio Test

Company	P^z		
	1%	5%	10%
	71.9273	55.2202	47.5877
HSBA	253.5003		
SAB	328.7881		
VOD	243.3971		
GLEN	223.8731		
PRU	290.8342		

Johansen's Test

Trace Test

The values for *r, the result statistic for the test, are provided in Table 21.*

Table 21. Johansen's Trace Test Results

Company	r = 0			r <= 1		
	1%	5%	10%	1%	5%	10%
	24.60	19.96	17.85	12.97	9.24	7.52
HSBA	98.60			29.65		
SAB	124.12			28.35		
VOD	79.86			34.35		
GLEN	165.34			34.16		
PRU	122.18			41.78		

All values for the r = 0 test fall significantly below the 1% threshold. Furthermore, all values for the r <= 1 test also fall below the 1% level, albeit by a smaller margin.

Maximum Eigenvalue

The values for *r, the result statistic for the test, are provided in Table 22. Similar to the trace test, the maximum eigenvalue results also yield large numbers falling significantly below the 1% cut off for both the r = 0 and r <= 1 tests for all stocks.*

Table 22. Johansen's Maximum Eigenvalue Test Results

Company	r = 0			r <= 1		
	1%	5%	10%	1%	5%	10%
	20.20	15.67	13.75	12.97	9.24	7.52
HSBA	68.95			29.65		
SAB	95.77			28.35		
VOD	45.50			34.35		
GLEN	131.18			34.16		
PRU	80.40			41.78		

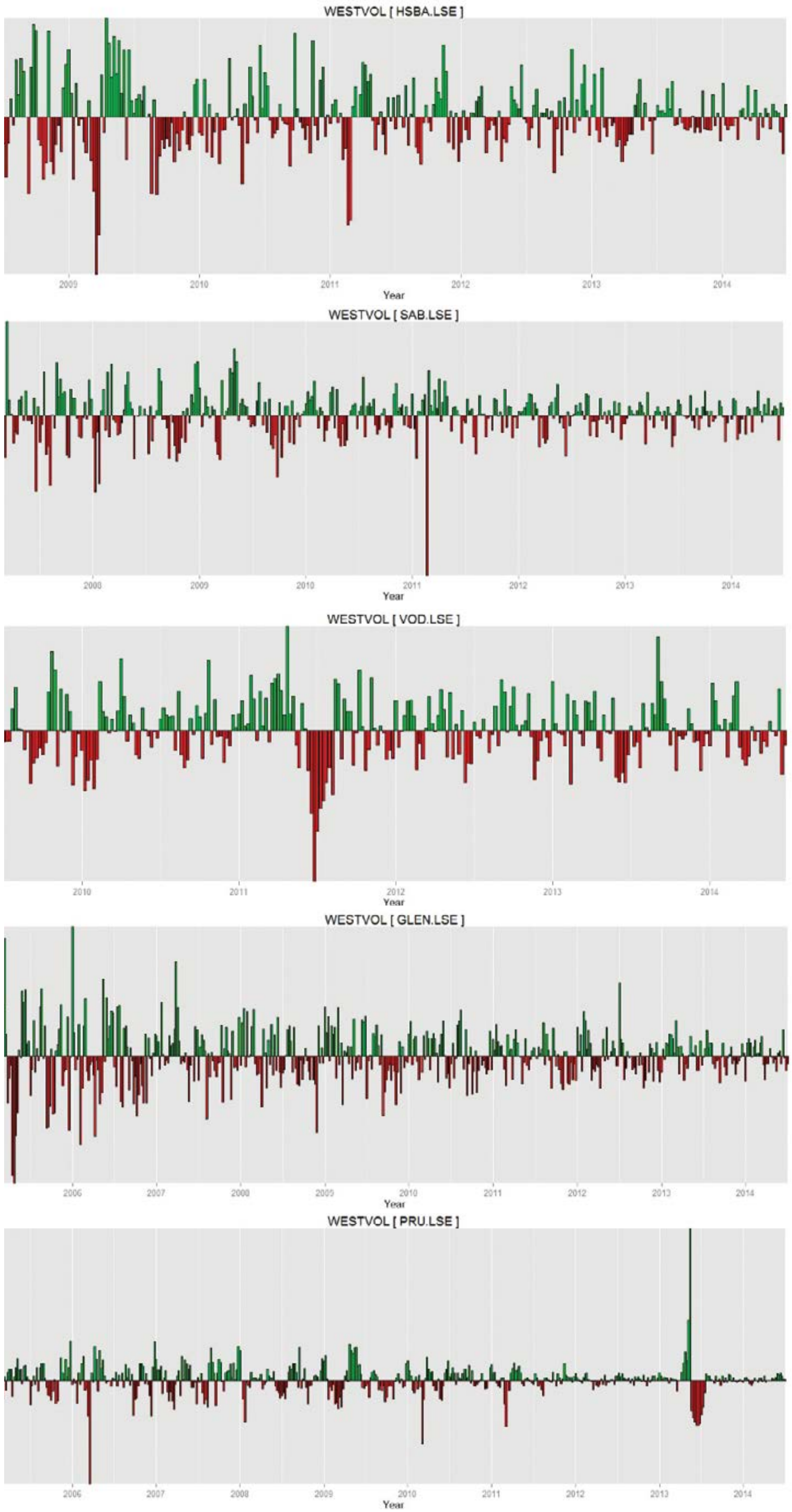
Hypothesis 2 Test: Forecasting

WESTVOL Indicator

The indicator is based on both the Web search and trading volume time series. The author starts the process by extracting a value for the trading volume from the Web search volume for each data item row. This produces a number, either positive when the search is higher than trading volume, or negative in the opposite situation; this is called the DIFF. In addition, the author also added a 10-period moving average (MA), which refers to weeks to reflect the weekly data, in order to further difference the set. Thus, the final WETSVOL indicator is depicted as a histogram in which the 0 line is when the DIFF equals the 10MA. Any deviations of the DIFF from the 10MA are used as signals.

For instance, if the DIFF is larger than the 10MA, then Web searches are on the rise and are depicted as green histogram bars on the indicator. In the case of falling searches, the histogram bar will be coloured red. Figure 4 depicts the WESTVOL indicator for all five stocks analysed in this report.

Figure 4. WESTVOL Indicator Results



Main Discussion and Analysis

Diagnostic Test

Standard Deviation

It appears that removing the seasonal component from Web search and trading volumes caused the Standard Deviation (SD) to fall significantly. The biggest decline of 98% was recorded for the HSBA series, in which most series averaged around a 92%–95% reduction in SD.

The indication from this operation is that the series became stabilised around its mean once seasonal adjustments were made to its constituents. Furthermore, comparing the series becomes easier once the standard deviations become smaller after the adjustments.

Auto-correlation

All stocks analysed under the ACF recorded a marginal auto-correlation in the magnitude of 0.11–0.15 on a scale of 1. The analysis provides invaluable information about the lag cut-off level, explaining that 1% to 1.5% of the lag xt variability would be explained by the preceding xt-1 variable. PACF plots provided similar outcomes; however, the author ultimately selected the AIC criterion to source the lag value.

The AIC values vary between stocks; however, it is apparent that the trading volume generally tends to auto-correlate later in time than the Web search, at least in the cases of HSBA, GLEN, and PRU. This indicates that trading volume tends to run cyclically at around 9–11 weeks for these stocks. It is worth noting that very low and almost identical values for the AIC lag for the VOD series would indicate a smooth dataset without any large departures from its mean.

Finally, the key interpretation of the lag order is that the series is likely to rise or fall above its average in week xt, provided the rise or fall also took place at xt-AIC.

Test for Normality

The Shapiro-Wilk results presented in Table 23 indicate that the H0 hypothesis can be rejected for all series, which confirms the series are normally distributed.

Table 23. Interpretation of Shapiro-Wilk Test Results

Company	Variable	Results Interpretation and Decision
HSBA	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
SAB	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
VOD	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
GLEN	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
PRU	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis

Moreover, the data appears to be positively skewed to the right for all series, except for the VOD trading volumes, which appear to be symmetric, as shown in Table 24.

Table 24. Interpretation of Mean, Median, and Mode in the Data

Company	Variable	Distribution
HSBA	Search	Positively skewed (to right)
	Volume	Positively skewed (to right)
SAB	Search	Positively skewed (to right)
	Volume	Positively skewed (to right)
VOD	Search	Positively skewed (to right)
	Volume	Symmetric
GLEN	Search	Positively skewed (to right)
	Volume	Positively skewed (to right)
PRU	Search	Positively skewed (to right)
	Volume	Positively skewed (to right)

Test for Unit Root

Augmented Dickey-Fuller

The trend term analysis in Table 25 indicates that all analysed series, apart from SAB Web search and GLEN trading volume, are stationary. The τ3, ø2, and ø3 statistics fall within the 5% level for SAB and the 10% level for GLEN, indicating the presence of a unit root in these series. The author would further difference these two series to bring them to stationarity.

The Drift Term results shown in Table 26 indicate that HSBA volume, VOD search and volume, GLEN search, and PRU volume exhibit signs of linear trends or drift in their data processes; therefore, the H0 hypothesis is rejected due to significant τ2 and ø1 statistics.

Lastly, the rejection of the H0 hypothesis of I(2) order of integration for all series in Table 27 implies that the first difference for all analysed series is stationary. In other words, the Web search and trading volumes are integrated for order one I(1).

Table 26. Interpretation of Augmented Dickey-Fuller

Company	Var	τ_2	$ø_1$
HSBA	Search	Accept H_0 hypothesis	Accept H_0 hypothesis
	Volume	Reject H_0 hypothesis	Reject H_0 hypothesis
SAB	Search	Accept H_0 hypothesis	Accept H_0 hypothesis
	Volume	Accept H_0 hypothesis	Accept H_0 hypothesis
VOD	Search	Reject H_0 hypothesis	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis	Reject H_0 hypothesis
GLEN	Search	Reject H_0 hypothesis	Reject H_0 hypothesis
	Volume	Accept H_0 hypothesis	Accept H_0 hypothesis
PRU	Search	Reject H_0 hypothesis	Reject H_0 hypothesis
	Volume	Accept H_0 hypothesis	Accept H_0 hypothesis

Drift Term Test Results

Table 27. Interpretation of Augmented Dickey-Fuller I(2) Test Results

Company	Var	τ_1
HSBA	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
SAB	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
VOD	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
GLEN	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
PRU	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis

Table 25. Interpretation of Augmented Dickey-Fuller Trend Term Test Results

Company	Var	τ_3	$ø_2$	$ø_3$
HSBA	Search	Reject H_0 hypothesis	Reject H_0 hypothesis	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis	Reject H_0 hypothesis	Reject H_0 hypothesis
SAB	Search	Accept H_0 hypothesis	Accept H_0 hypothesis	Accept H_0 hypothesis
	Volume	Reject H_0 hypothesis	Reject H_0 hypothesis	Reject H_0 hypothesis
VOD	Search	Reject H_0 hypothesis	Reject H_0 hypothesis	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis	Reject H_0 hypothesis	Reject H_0 hypothesis
GLEN	Search	Reject H_0 hypothesis	Reject H_0 hypothesis	Reject H_0 hypothesis
	Volume	Accept H_0 hypothesis	Accept H_0 hypothesis	Accept H_0 hypothesis
PRU	Search	Reject H_0 hypothesis	Reject H_0 hypothesis	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis	Reject H_0 hypothesis	Reject H_0 hypothesis

Philips-Perron

The Philips-Perron Trend Model test reveals that the H0 hypothesis for presence of a unit root could be rejected for all series, as Table 28 describes. This is in minor contrast to the ADF result in which two series (SAB and GLEN) had to be differenced to achieve stationarity.

Table 28. Interpretation of Philips-Perron Trend Model Test Results

Company	Var	$Z(\tau_\alpha)$
HSBA	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
SAB	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
VOD	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
GLEN	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
PRU	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis

However, once the author dropped the trend component and analysed the series for drift presence, the results in Table 29 indicated that neither drift nor linear trend is present in any of the series analysed.

Table 29. Interpretation of Philips-Perron No-Trend Model Test Results

Company	Var	$Z(\tau_\mu)$
HSBA	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
SAB	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
VOD	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
GLEN	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
PRU	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis

Lastly, further series differencing produced $Z(\tau\beta)$ within the rejection level for all series, indicating stationarity in the data and first order of integration, I(1). Therefore, the H0 hypothesis for presence of non-stationarity was rejected in Table 30.

Table 30. Interpretation of the Philips-Perron Series Differencing Test Results

Company	Var	$Z(\tau_\beta)$
HSBA	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
SAB	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
VOD	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
GLEN	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
PRU	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis

Hypothesis 1 Test: Co-integration

Engle-Granger

A relatively strong correlation of 20.7% and 18.7% in the cases of SAB and HSBA, respectively, indicates that changes in trading volume could, to some extent, be explained by movements in Web searches. The p-value of 16 decimal places for the two stocks makes this result very significant in that respect; however, other stocks fared much worse for that test, with correlations of 5% or less.

Analysis of co-integration between the two series reveals the H0 hypothesis of no co-integration had to be rejected for all series, except for GLEN, as Table 31 shows.

Table 31. Interpretation of Engle-Granger OLS Estimation Co-Integration Test Results

Company	Var	τ_1
HSBA	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
SAB	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
VOD	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis
GLEN	Search	Reject H_0 hypothesis
	Volume	Accept H_0 hypothesis
PRU	Search	Reject H_0 hypothesis
	Volume	Reject H_0 hypothesis

The Error-Correction Model (ECM) results provided a very strong clue to the relationship between Web searches and trading volumes; more specifically though, the direction of that relationship is also known as the direction of causation. The ECM reveals that only HSBA and SAB values of -0.005469 and -0.07026, respectively, show elements of co-integration due to the negative sign in the result. This information, coupled with relatively strong correlations for the two stocks, instils the author with confidence that a Web search could have predicting power on trading volumes for these two stocks.

Philips-Ouliaris

Tests for the Variance and Multivariate Ratios suggest rejecting the H0 hypothesis of no co-integration in favour of the alternative that co-integration is present in all sampled stocks, as depicted in Table 32.

Table 32. Interpretation of Philips-Ouliaris Variance and Multivariate Test Results

Company	$\hat{P}u$	$\hat{P}z$
HSBA	Reject H_0 hypothesis	Reject H_0 hypothesis
SAB	Reject H_0 hypothesis	Reject H_0 hypothesis
VOD	Reject H_0 hypothesis	Reject H_0 hypothesis
GLEN	Reject H_0 hypothesis	Reject H_0 hypothesis
PRU	Reject H_0 hypothesis	Reject H_0 hypothesis

Johansen's Trace Test

Finally, the Trace and Maximum Eigenvalue tests, shown in Table 33, uniformly suggest co-integration between Web searches and trading volumes for all companies analysed in this study.

Table 33. Interpretation of Johansen's Trace and Maximum Eigenvalue Test Results

Company	r = 0	r <= 1
HSBA	Reject H_0 hypothesis	Reject H_0 hypothesis
SAB	Reject H_0 hypothesis	Reject H_0 hypothesis
VOD	Reject H_0 hypothesis	Reject H_0 hypothesis
GLEN	Reject H_0 hypothesis	Reject H_0 hypothesis
PRU	Reject H_0 hypothesis	Reject H_0 hypothesis

This result also confirms the Engle-Granger and Philip-Ouliaris findings; however, only HSBA and SAB would be regarded as most reliable sets due to the high correlation figures.

Furthermore, the fact that the H0 hypothesis was rejected for the r <= 1 test suggests the presence of more than one co-integrating vector. Therefore, this also favours HSBA and SAB only because the ECM test had suggested causation from the Web search to trading volumes for just these two companies.

Hypothesis 1: Summary

Analysis of Hypothesis 1 concludes that only two companies show relatively strong co-integration and causation from Web searches to trading volumes. Due to the weak correlation figures for VOD, GLEN, and PRU, as well as the wrong direction for their co-integration results, the author had to accept the H0 hypothesis that the level of co-integration of Web search volumes and stock trading volumes for these companies is not significant. Table 34 shows the results for all companies analysed in this study.

Table 34. Interpretation of Hypothesis 1

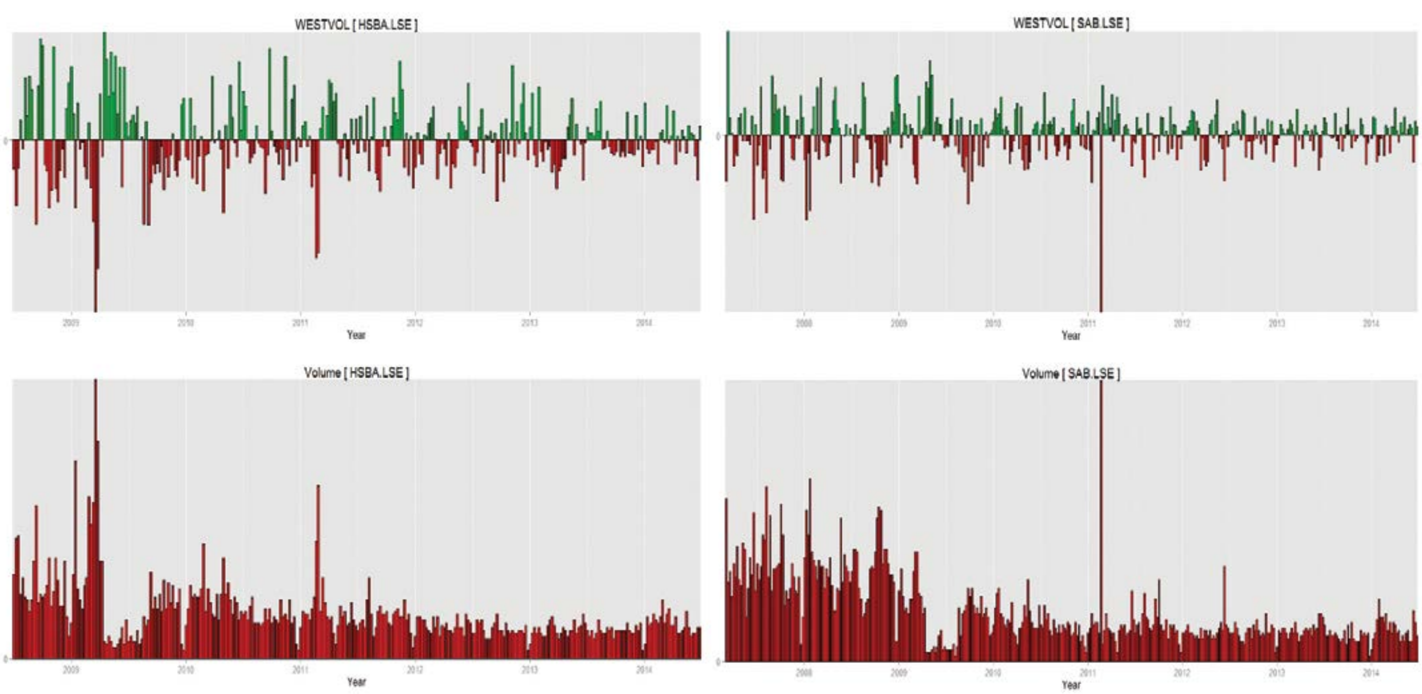
Company	H_0: The level of co-integration of Web search volumes and stock trading volumes for selected stocks traded on LSE is not significant. H_1: The level of co-integration of Web search volumes and stock trading volumes for selected stocks traded on LSE is significant.
HSBA	Reject H_0 hypothesis
SAB	Reject H_0 hypothesis
VOD	Accept H_0 hypothesis
GLEN	Accept H_0 hypothesis
PRU	Accept H_0 hypothesis

Hypothesis 2 Test: Forecasting

WESTVOL Indicator

The Hypothesis 2 test involves analysis of the WESTVOL indicator accompanied by trading volumes for HSBA and SAB. At this stage, the author had to visually inspect the chart. Figure 5 shows the WESTVOL indicator and corresponding trading volume, unannotated.

Figure 5. WESTVOL and Trading Volume Unannotated



In Figure 6 for HSBA, the author depicts one proposed way of interpreting the WESTVOL, in which a set of green/red bars in a blue box indicate that the WESTVOL is changing its direction and crosses the 0 signal line down. The black arrows indicate spikes in trading volume at the time of the down crossover of the 0 signal line when the bar changes from green to red on WESTVOL.

Figure 6. WESTVOL and Trading Volume for HSBA Interpretation 1

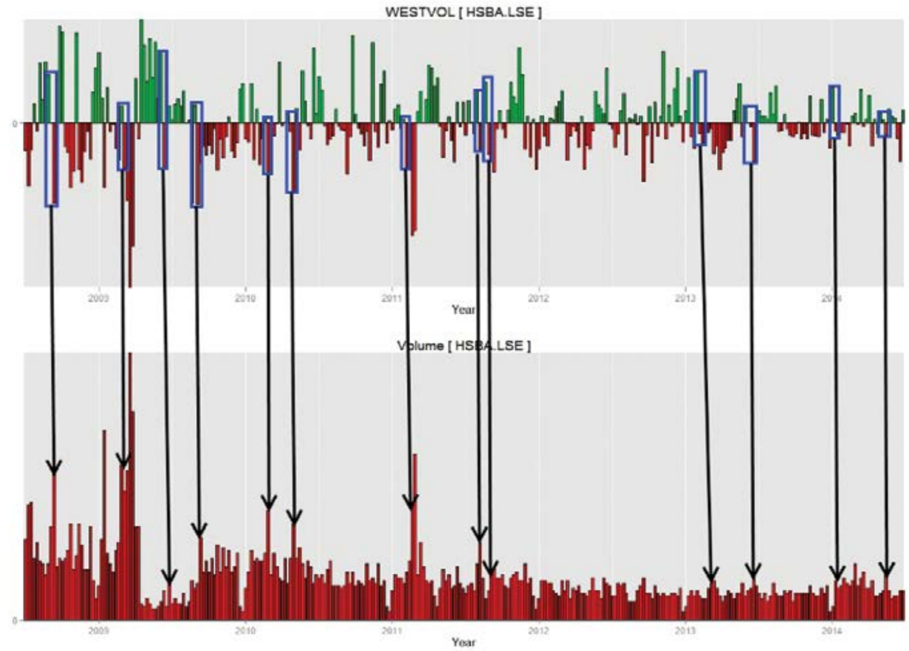
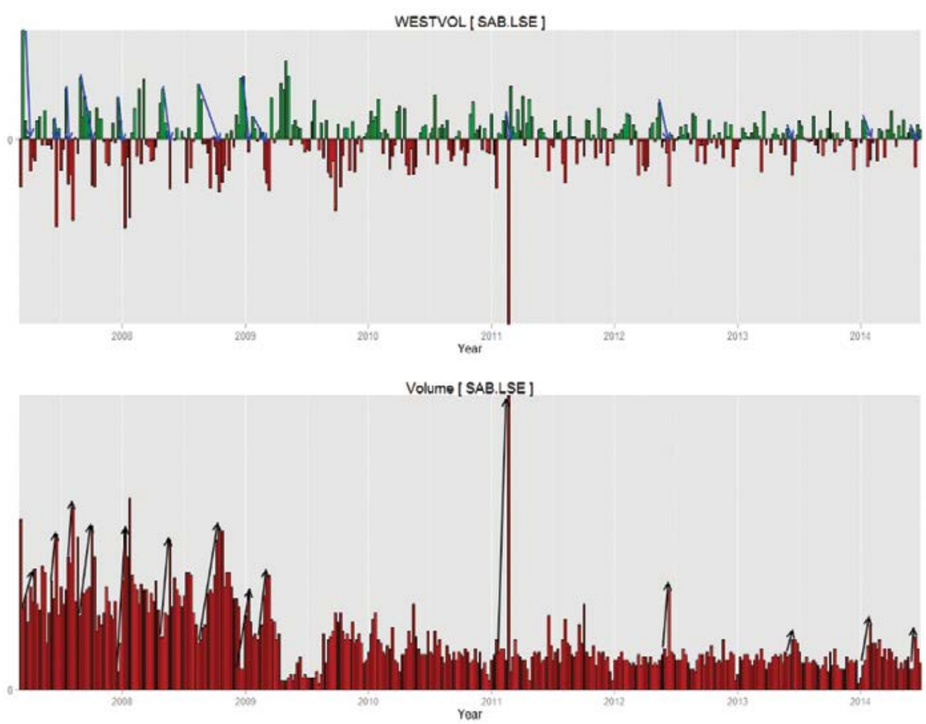


Figure 7 for SAB shows a second way of interpreting WESTVOL signals, in which the blue, pointing-down, arrows show the Web search easing down and the WESTVOL crossing down the 0 signal line. At the time of the down crossover, trading volume tends to pick up, as indicated by the black pointing-up arrow.

Figure 7. WESTVOL and Trading Volume for SAB Interpretation 2



Application of WESTVOL appears to prove Hypothesis 2 and that there is some forecasting power in the Web search volumes on the trading volumes for the selected stocks. Therefore, the author rejects the H0 hypothesis that the forecasting power of Web search volumes on stock trading volumes for selected stocks traded on LSE is not significant for both HSBA and SAB. Table 35 summarises the final outcomes of this test.

Table 35. Interpretation of Hypothesis 2

Company	H_0: The forecasting power of Web search volumes on stock trading volumes for selected stocks traded on LSE is not significant. H_1: The forecasting power of Web search volumes on stock trading volumes for selected stocks traded on LSE is significant.
HSBA	Reject H_0 hypothesis
SAB	Reject H_0 hypothesis

Interpretation of Findings

Diagnostic Test

DeFusco (2007) argued that standard deviation is a measure of the dispersion of values around their mean and that it tends to decrease once trends and seasonal components are removed. Additionally, the author noticed that a low standard deviation resulting from decomposing the series also made the data stationary (Cowpertwait and Metcalfe, 2009).

Both the Web search and trading volume series displayed characteristics of a random walk with a stochastic trend; consequently, co-integration was not possible due to non-stationarity in the series, especially for the SAB and GLEN examples. Closer investigation of the trend component of the SAB Web search and GLEN share trading volumes found one plausible explanation behind this discovery. This showed the series commencing at a high level and then trending downwards to never reach previous highs again; therefore, a constant downward trend was maintained through the series.

Test for Unit Root

The examples of SAB and GLEN manifested a unit root presence, indicating non-stationarity in the data. The process for differencing the data made the series stationary (Ssekuma, 2011) and removed the stochastic component (Pfaff, 2008). The fact that hypotheses could be evaluated while undertaking the Augmented Dickey-Fuller and Philips-Perron tests made the evaluation process unbiased. Furthermore, the programmatically deducted Akaike Information Criterion allowed more valuable results and yet again helped in reaching unbiased conclusions.

Hypothesis 1 Test: Co-integration

The author shows in this study that high correlation is, to some extent, a valuable pre-requisite of co-integration. The two highest correlated stocks, SAB (45.7%) and HSBA (43.6%), ultimately showed strong signs of co-integration once Web searches were regressed on the trading volumes. In contrast, the reasons behind low correlations for the remaining three stocks (VOD, GLEN, and PRU) could be partially explained by lower market caps for these stocks, representing lower search activity and interest in these stocks.

Hypothesis 2 Test: Forecasting

Finally, HSBA and SAB were the only two stocks fulfilling the author's criteria for WESTVOL implementation, since their ECM figures confirmed correct order of regression; their R-squared values were the highest amongst all subjects; and the Engle-Granger, Philips-Ouliaris, and Johansen tests uniformly confirmed signs of co-integration of their Web search and trading volume series.

Ultimately, the WESTVOL indicator has shown that crossovers of the signal line predict shifts in trading volume; however, interpretation of the signal is still open for a debate, as the indicator was only interrogated visually. On a cautionary note, this indicator is used to forecast increasing volatility in share trading, as measured by increases in trading volumes; therefore, one's entry point and direction of trade need to be put in the context of the share's technical situation.

Limitations of the Study

Saunders, Lewis, and Thornhill (2009) argue that virtually all studies have limitations, and the author is aware this study is not an exception to this argument, as it only focused on a selection of five stocks that were hand-picked and based on the highest market cap value. As already indicated, the market cap criterion proved to be crucial because Web search data still lacks predicting power when it comes to less searched stocks, even considering FTSE 100 constituents. A further point regarding Web search data is that it only spans back to 2004, in which the author found periods of zero searches being relatively common for most FTSE 100 stocks. Moreover, the data is only available in weekly timeframes, which makes the efforts of creating a trading indicator even more difficult, as the weekly timeframe is not really suited to short-term traders. However, the author believes foundations have been provided for further analysis, either for a long-term-oriented investor or once daily Web search data grows in volume and availability.

Recommendations

In the author's opinion, this research has opened a potential door for further integrations of Web searches with stock market data. The limitations mentioned above provide ample opportunities for different approaches; however, the data availability limitation will remain until Web search databases finally advance into daily segmentation or perhaps even real-time. Firstly, a different selection of financial instruments for research could possibly be recommended, and analysis could perhaps be undertaken on co-integration at the sector or index level. Multinational and geographical searches could also be employed at this stage. Secondly, keyword selection could employ different criteria; for instance, company or product names could be regressed against trading volume. Additionally, searches for news relating to companies could possibly provide profitable trading opportunities.

Conclusion

This research utilised a programmatic approach to econometric analysis: in this case, co-integration of Web searches with stock trading volumes. The author employed a powerful language R to script all the tests, perform analysis, and display the findings graphically. The processes have been applied to five of the largest stocks traded on the London Stock Exchange and, ultimately, a new indicator called WESTVOL was proposed as a means of forecasting trading volume.

Even though a number of limitations were highlighted, the final derivative of this writing was that two stocks—HSBA and SAB—showed that Web search activities can predict trading volumes. The remaining three stocks—VOD, GLEN, and PRU—displayed very weak correlation at the start and were followed by the wrong regression order. However, with regard to the limitations of this study, recommendations were presented in the light of these findings to facilitate further development in this area.

In summary, through the methodologies employed, the author revealed that Web search volumes and stock trading volumes are co-integrated, as the examples of HSBA and SAB indicate. Through the examples of these two stocks, the author has proven that Web searches hold forecasting attributes on the trading volumes. However, it remains to be seen and anticipated that further research follows suit in the investigation of the predictive power of Web searches on trading volumes or any other microeconomic variable.

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Entry Filtering With Volatility Measures: A Thorough Analysis of Volatility Filters in Conjunction With a High Probability Mean Reversal System

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Abstract

Five historical volatility filters are thoroughly analysed in conjunction with a high probability mean reversal system. Results highlight the high potential of Williams' VIX Fix for long systems, the quality of Average True Range as well as Candlestick Chart Volatility for short systems, and the relative inaptitude of Historical Volatility in both directions. Moreover, combining indicators appears beneficial only for positions going against the broad market.

Introduction

Evoking market volatility in a conversation with investors surely results in volatile reactions: Some will probably say they embrace rapid market moves and high uncertainty; others will perhaps tear their hair out and remember stressful events. One thing is certain, consensus does not exist regarding volatility, even in the technical universe.

Technical authors often suggest filtering system entries to avoid risk or increase profits. Widely used filters include seasonality, long-term trend, and volatility. Technical studies have mainly looked at the latter in conjunction with trend continuation. This paper takes a different approach by integrating five volatility algorithms into a basic mean reversal system and, based on six key performance metrics, ranks the systems and their filters relatively (Is an indicator outperforming its peers?). The approach distinguishes between long and short systems (Do filters behave differently for up and down reversals?) and considers as filters every indicator's value and slope in absolute and relative terms (Is combining filters better than pushing single-indicator limits?).

Results are not always consistent but tend to indicate that answers to the three questions are: Yes, some indicators regularly outperform others; Yes, volatility filters behave differently in up and down markets; and No, the results vary widely from one test to the other.

Section two of the paper introduces the tested volatility indicators, section three details the methodology to obtain the results presented in section four, and section five concludes.

Price History Based Volatility Indicators

A first question that arises is: What is volatility? The Cambridge dictionary defines something volatile as *likely to change suddenly and unexpectedly,* while the OECD sees volatility as a *measure of the risk or uncertainty faced by participants in financial markets.* In this paper, volatility is defined as *a measure of variability that quantifies risk and opportunity usually without any directional considerations*. Therefore, "increased volatility" usually does not indicate the direction, but acknowledges that price moves accelerate.

Volatility is, nevertheless, a broad term that encompasses multiple coexisting concepts. Implied volatility is derived from option prices and the Black and Scholes formula, and reflects the expected asset volatility between now and the option's expiration. Historical volatility is calculated through the asset price history and reflects past movements, which include all information. Relative volatility can, on the one hand, refer to a comparison of similar formulas with different lookback periods, and on the other hand, denote the correlation coefficient between two time series (often referred to as Beta). This paper focuses on historical volatility indicators.

A second question that can be asked is: Is volatility good or bad? When judging volatility on its own, different answers have been given. On the one hand, Sharpe and Markowitz believe that higher volatility, without distinguishing between up- and downside variability, comes along with a riskier, more uncertain investment. On the other hand, some practitioners do not see high volatility as riskier, as the impact of an investment on the portfolio can be mitigated by the allocation size. Risk, for Scot Billington,[1] is the difference between anticipated and realized worst loss. With this risk definition in mind, low volatility comes with higher risks. A different approach to answering the question is taken by Thomas Stridsman,[2] who looks at volatility levels in conjunction with the position that good volatility works for a position and bad volatility indicates higher variability with either no, or worse, opposite direction price moves.

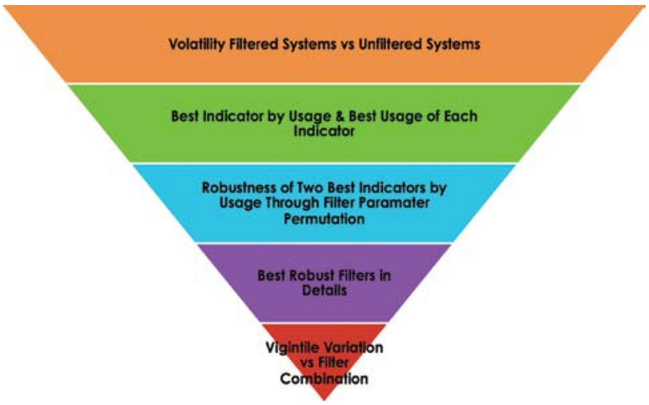
Many algorithms, each focusing on price action specificities, attempt to quantify risk and opportunity. Formulas always include a time parameter that can potentially heavily impact the volatility measure, and can use single or multiple price series or even concentrate on specific points from the chosen time horizon.[3]

Perry Kaufman[4] introduces five historical volatility measures in his book: the change in price over *n* days, the maximum price fluctuation over *n* days, the average true range during *n* days, the sum of absolute price changes over *n* days, and the classic annualized volatility. In this paper's definition, the price change over *n* days is considered an unusual volatility indicator as it gives a trend indication. Other well-known volatility indicators are Donald Dorsey's Relative Volatility Index, Marc Chaikin's Chaikin Volatility, and Alexander Elder's Thermometer.

Tests concern five different indicators; three are widely used and introduced by Kaufman (Average True Range, Historical Volatility, and Range), one is similar to the sum of absolute price changes (Candlestick Chart Volatility),[5] and one tries to replicate the VIX (Larry Williams' VIX Fix),[6] Noteworthy is that Williams' VIX Fix passes the paper's volatility definition but includes a directional bias by taking a low (high) value when near (far from) the lookback period's high.

Methodology

Figure 1. methodology for discovering best in class volatility filters and potential combinations



Test Environment

The different tests are conducted in AmiBroker v5.90 with Norgate Investor Service's Premium Data. The selected stocks include Russell 3000 constituents from November 2014 and U.S. delisted stocks that are adjusted for capital related corporate actions (splits, reverse splits, capital returns, special dividends, stock dividends, demergers, and spinoffs). The simulation runs from the 1st of January 2004 until the 31st of October 2014 on daily data.

To be considered for the portfolio, the stock needs a one-month liquidity above $10m and a close price superior to $5. Moreover, every single transaction has a cost of 0.15% of the position size to account for commission and slippage. The initial equity is set at $1m and uninvested money does not bear interests.

System

In addition to the aforementioned requirements, the long-only (short-only) system entry needs a 5-day simple moving average (SMA) of the 3-day Relative Strength Index (RSI) to be between 5 (85) and 15 (95). The portfolio is composed of maximum 10 stocks each with a 10% capital allocation, thus avoiding any margin and position pyramiding. The stocks that pass the criteria are ranked with a 5-period SMA of the 3-week RSI: For the long-only (short-only) system, how higher (lower) the weekly indicator, how better the rank of the criteria-fulfilling stock. The quantity of best ranked stocks added to the portfolio depends on available equity. The system enters the position the next morning at open price.

Four exit mechanisms are used in the system. First, a regular exit takes place in the long-only (short-only) system when the close crosses the 5-day high (low) SMA. Second, exits occur on the last quotation day of delisted stocks. Third, a 20-day time stop avoids keeping funds in non-moving stocks. Finally, a static stop loss counters losing signals. The stop loss uses the True Range Double (TRD) concept introduced by Cynthia Kase[7] and equals one time the 20-day average TRD plus one time the 20-day TRD SD away from the entry price. The close serves as the exit price except in the fourth case for which exit occurs intraday. Besides, the system does not use any re-entry delays after a trade.

Indicator Assessment

To test the added value of the indicators, the initial system is compared with systems that incorporate the volatility measures

Table 1. Five tested historical volatility indicators with their parameters and rationale

Indicator	Short Name	Formula	Parameter	Underlying Theory
Average True Range	ATR	MA (Max (H_t, C_{t-1}) – Min (L_t, C_{t-1}), N)	N = 14	Maximum Inter-Day Move
Historical Volatility	HV	SD (LN (C_t / C_{t-1}), N) * √252	N = 21, C	Dispersion Around Average Price
Candlestick Chart Volatility	CCV	MA (DF, N)/MA(C, N) ; with DF for up-day = $\lvert C_{t-1} - O_t\rvert + \lvert O_t - L_t\rvert + \lvert L_t - H_t\rvert + \lvert H_t - C_t\rvert$, for down-day = $\lvert C_{t-1} - O_t\rvert + \lvert O_t - H_t\rvert + \lvert H_t - L_t\rvert + \lvert L_t - C_t\rvert$	N = 22	Refinement of Sum of Absolute Price Changes with Direction Assumption and 4 Price Series
Range	R	Highest (H, N) – Lowest (L, N)	N = 22	Maximum Extension in Period
Williams' VIX Fix	WVF	(Highest (C, N) - L_t) / Highest (C, N)*100	N = 22	VIX Replication

Table 2. Indicator boundaries for the three tested quantiles

<table>
<tr><th></th><th colspan="5">Value</th><th colspan="5">Slope (10-day linear regression*100)</th></tr>
<tr><td>Percentile</td><td>ATR</td><td>HV</td><td>CCV</td><td>R</td><td>WVF</td><td>ATR</td><td>HV</td><td>CCV</td><td>R</td><td>WVF</td></tr>
<tr><td>0.2</td><td>1.9</td><td>18</td><td>3.2</td><td>8</td><td>2.2</td><td>-5</td><td>-60</td><td>-6</td><td>-50</td><td>-40</td></tr>
<tr><td>0.4</td><td>2.5</td><td>25</td><td>4.3</td><td>12</td><td rowspan="2">5.3</td><td>-1.5</td><td>-15</td><td>-1.75</td><td>-10</td><td rowspan="2">0</td></tr>
<tr><td>0.6</td><td>3.4</td><td>34</td><td>5.7</td><td>17</td><td>1.5</td><td>15</td><td>1.75</td><td>10</td></tr>
<tr><td>0.8</td><td>4.7</td><td>50</td><td>7.9</td><td>26</td><td>12.0</td><td>5</td><td>60</td><td>6</td><td>50</td><td>40</td></tr>
</table>

in four different ways, referred to as indicator usages: absolute value (AV), absolute slope (AS), relative value (RV), and relative slope (RS).

On the one hand, absolute classifications require each indicator's quantile limits that are obtained from 100 randomly selected Russell 3000 constituents for the test period. The methodology applies both for the indicator's value and slope, which are defined as the 10-day linear regression slopes of values and multiplied by 100 for precision purposes. Obtained values are then rounded to one decimal or one unit, and slopes, which are approximately symmetric, use a number in between the absolute value of symmetric quantiles. Rounding the obtained numbers departs from the exact quantile limits but gives clearer limits; on the other hand, relative classifications use the 60-day cumulative distribution of the indicator's slope and value to define filter levels.

The first, third, and fifth quantile limits are added to the entry rules of both systems, which results in 120 system tests. Due to its directionality, the WVF requires its 20th, 50th, and 80th percentiles, with the former (latter) two the bounds for the short (long) systems. The three WVF tests from a specific indicator usage thus cover the whole spectrum of stocks, whereas the four other indicators are restricted to 60 percent of indicator values. Each system category (e.g., long AV or short RS) is then appraised through six different measures. The first measure looks at the system from a game theory point of view: the Kelly Criteria is a formula that provides the optimal position allocation to increase long-term wealth. The two ensuing measures emphasis the risk-reward relationship inherent to the system: D3 and risk-reward ratio. The former relates compounded growth rate to exposure and average drawdown (similar to TradeStation's Rina without filtering positive trades), while the latter checks for the variability of the expected return. Furthermore, Recovery Factor and Average Drawdown (ADD) check the risks associated to the systems. The last measure, Welch's T-statistic of trade results, focuses on individual trades relative to the unfiltered system.

Discovering best in class individual indicators and combinations of volatility filters is a six-step process, most using relative ranking of filters based on the six key metrics.

First, filtered systems are compared with the unfiltered strategies. The ranking by usage and key metric of the unfiltered system illustrates how well filters work. If a particular volatility level is beneficial to the mean reversing system, and the five indicators add value to the system, the unfiltered system's rank should be sixth. A higher ranking indicates unequal volatility measures, and a lower ranking shows that the original system suffers from trades in a particular quantile of the usage.

Second, the indicators are analysed in two ways. On the one hand, a table summarises which indicators perform well and poorly with a particular usage and potentially indicates systematic dominance of one indicator. On the other hand, all usages of one indicator are compared in order to obtain the optimal mean reversal indicator configuration.

Third, the two best ranked filters by usage are selected for additional tests similar to Dave Walton's System Parameter Permutation[8] but restricting the permutation to the volatility filter. As stated, "care must be taken to thoughtfully select parameter scan ranges ex-ante." As a consequence, the simulations linearly divide the values between the previous and following deciles to obtain 10 iterations and their median and average key metrics (e.g., confines vary from the 70th to the 90th percentile for a fifth quantile indicator). The approach helps clarify robustness of previous results, but also benefits absolute

Table 3. Introduction to key metrics used for assessing volatility filter performance

Key Metric	Formula	Purpose/Comment
Kelly Criterion	((R+1) * P -1) / R with R = Average Win/Average Loss (Payoff Ratio) P = Win Percentage	Maximum long-term profit; Better with stable parameters—The higher the better
D3	CAR / (E% * (- ADD)) with CAR= Compounded Aggregate Return E% = Exposure Percentage ADD = Average Drawdown	Relates profit capacity with exposure and ability to consistently increase—the higher the better
Risk Reward Ratio	ELS/SE with ELS = Equity Line Slope (Expected Annual Return) SE = Equity Line Standard Error	Relation of inherent system risk and potential reward
Recovery Factor	Net Profit/Maximum System Drawdown	Gain capacity vs. maximum loss
Average Drawdown	1/N *∑ (E – HE)/HE with N = Amount of Days in Simulation HE = Highest Equity Between Start and Day N E = Equity on Day N	Looks at consistency of equity growth and ability not to incur losses—the higher the better
Welch's T-test	(APF – AP)/Suf with APF = Average Profit Filtered System AP = Average Profit Unfiltered System Suf = Square Root ((Variance Filtered System/Q trades Filtered System) + (Variance Unfiltered System/Q trades Unfiltered System))	Checks individual trade potential; Minimum trades in a system is 801, implying significance levels approximation with Z-Stat; Serves for relative system classification too

indicator usages that have fatter tails. The mean and median key metrics are then averaged and relatively ranked to obtain the three best long and short filters.

Fourth, these six systems are studied thoroughly to gain more insight on how the filters work. The tests look at the 12-month information ratio of the filtered system in comparison with its unfiltered counterpart excess returns, and their 12-month serial correlation, excess returns in comparison with the Russell 3000 performance as well as cumulative distribution functions of the trades.

Fifth, the three best filters' boundaries are changed to the three higher and lower vigintile limits and combined with other filters from the third step. The three best boundary variations and combinations are then relatively ranked using the key metrics. The purpose of the ranking is to find out if indicator combinations have more benefits than using extremer conditions in one indicator.

Finally, the fifth step systems are verified on earlier data and subsets of the stocks to find out how robust the results are.

Results

Volatility Filtering?

Without filters, the long system manages a risk-adjusted profit of 13.18% annually, trades 5,029 times, and has a mean profit of 0.287%. The short system is not as successful, with an annual risk-adjusted loss of 5.98%, 4,723 trades, and a mean loss of -0.091%.[9] Lower transaction costs would thus yield positive results for the short system.

Table 4. Unfiltered vs. filtered systems: ranking of unfiltered system by indicator use and key metric out of 16 systems *(power numbers in t-stat indicate the quantity of significant improvements at 10% significance, number reflects mean profit rank)*

	LAV	LAS	LRV	LRS	SAV	SAS	SRV	SRS
Kelly	2	2	1	2	6	3	3	3
D3	2	2	1	2	6	3	4	2
Risk-Reward	1	2	1	2	5	2	2	1
Recovery Factor	2	2	1	1	6	7	7	5
ADD	6	3	2	3	5	4	4	4
Welch's T-Stat	2^0	1	1	2^0	6^2	3^1	6^0	3^0
No Filter System	1	1	1	2	6	3	4	3

As filters improve the short system more than the long system, which is logical considering the stand-alone systems' respective performance, the enhancement potential of volatility filter quantiles on better systems remains uncertain. Interestingly, the only filtered strategy that manages to beat the long system requires a low relative ATR slope. The most improved key metric is ADD, with a responsible first quantile absolute value and slope environments in long systems and by contrast, high volatility in short systems. Only three of the 16 systems that improve mean profit do so at a 10% significance level, and these are all short and absolute by nature.

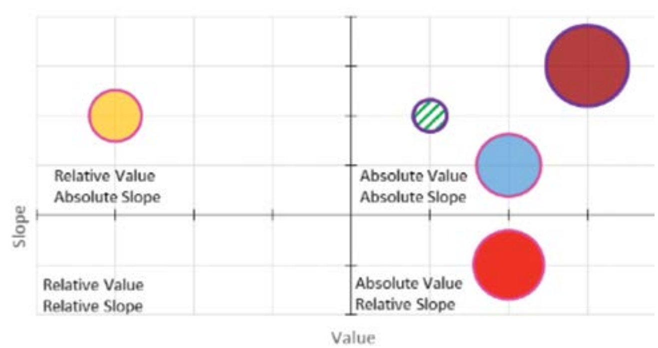
Table 5. Three Best and worst filters and their quantile by usage *(wvf has high, moderate, or low instead of a quantile as a consequence of its different testing methodology)*

Position	LAV	LAS	LRV	LRS	SAV	SAS	SRV	SRS
1	WVF H	CCV 1	WVF H	ATR 1	ATR 5	ATR 1	R 3	CCV 3
2	WVF M	WVF H	HV 1	WVF H	CCV 5	R 1	WVF M	ATR 1
3	HV 1	R 3	R 5	WVF L	WVF H	HV 1	ATR 3	CCV 1
13	ATR 5	CCV 5	HV 5	HV 3	ATR 1	CCV 3	ATR 5	CCV 5
14	HV 5	HV 5	R 3	CCV 5	CCV 1	R 5	CCV 5	ATR 5
15	CCV 5	ATR 5	ATR 5	ATR 5	R 1	HV 5	HV 5	HV 5

Choice of Volatility Measure and How to Use the Indicators

Table 5 illustrates four characteristics of the volatility filters. First, WVF times market bottoms well, with half of the top three filtered long systems using the indicator. The AV usage is particularly helpful, as shown by the first and second positions. Nevertheless, the directionality of the WVF, and as a consequence, its different boundaries, impacts moderate results. Moreover, the same indicator does not help as much for down trades, and a high AV also seems beneficial to the short system. Second, high value and slope affect potential long profits: 10 out of 12 worst filters belong in the fifth quantile. The presence of the fifth quantile relative range value in the top three indicates that a high absolute value seems worse than a high relative value. Third, low absolute and relative slopes benefit both long and short systems: 10 out of 12 worst slope systems are from the fifth quantile. Fourth, high ATR and CCV AV work particularly well with short mean reversals, and as a result, their optimal usage contrasts heavily with upward reversals. Finally, high HV value and slope are often amongst the worst performing filters and often have lower win percentages, which points toward a higher probability of trend continuation in these systems.

Figure 2. Long system: indicator best usage [greater bubble size reflects better relative average key metric ranking of the two best indicator usages, and purple (pink) border colour indicates better results with the value (slope) of the indicator]



The first, second, and third gridlines away from the axis cross represent low, moderate, and high indicator values and slopes. The bubble size reflects the relative rank of the best value and slope filters for each indicator (e.g., the ATR low RS has the best rank and the ATR moderate AV the ninth rank out of 10 systems), which gives ATR a lower average rank than the WVF. Figure 2 clarifies at least four important characteristics of the volatility filters in conjunction with a long mean reversal system. First, CCV, HV, and WVF work best when used absolutely for both value and slope, whereas ATR prefers RS to AS and R RV to AV. Second, no indicator has the same reading level preferences. Low slopes work well for ATR and CCV, moderate slopes for R and HV, and, not surprisingly, WVF favours high slopes. The same remark is valid for indicator value: low readings of HV ensure better results; moderate values of CCV and ATR and high R and WVF do the same. Third, HV is the worst filter, as it is relatively weak in all key metrics with the exception of ADD for the value system. WVF, however, shows more promise in all fields but ADD. Finally, CCV and ATR are the most similar indicators. ATR manages better results for both value and slope though.

Figure 3. Short system: indicator best usage [greater bubble size reflects better relative average key metric ranking of the two best indicator usages and purple (pink) border colour indicates better results with the value (slope) of the indicator]

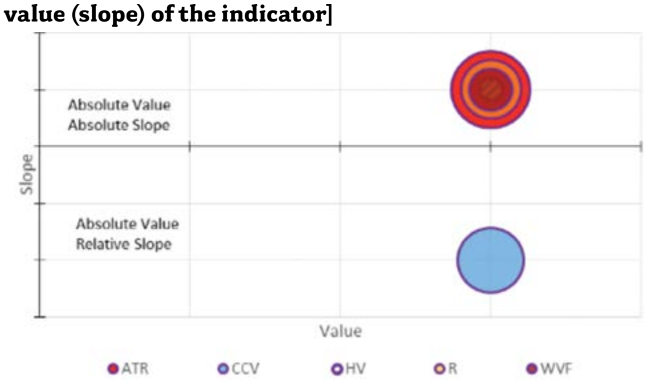


Figure 3 illustrates a different indicator behaviour for short mean reversals. First, all indicators with the exception of CCV prefer AV and AS over RV and RS, and all require high volatility value, which works better than slope. Second, HV again compares poorly with the other indicators, and while it slightly improves the original system, the indicator is, along with R, unable to create a profitable system. Third, WVF is the second worst overall indicator for short mean reversals. The overall ranking is however badly influenced by the low AS filter, which scores the worst in every key metric. Finally, CCV AV behaviour again mimics ATR with slightly worse results.

Two Best Filters by Usage and Their Robustness

Table 6 shows the strong dominance of the WVF for the long system with four of the five best filters. The AV is particularly understated, with the average key metric 28.9% higher and the best performance coming with slightly higher values. Only a low CCV AS is able to filter long signals as well. CCV also seems more robust than ATR, as shown by its robustness performance for the short system. The indicator's high AV in the short system manages the best average and median values in the six key metrics. ATR manages impressive consistency around its 80th percentile but rapidly loses performance further away in both directions. Noteworthy is that R AS benefits from more extreme values but does not manage to perform as well as the two AV filters, and ATR AS, on the contrary, benefits from a leaner limit. Moreover, relative filters consistently underperform their absolute counterparts.

Table 6. Indicator classification after regrouping of two best filters by usage and filter parameter permutation

	Long		Short	
1	AV	WVF 5	AV	CCV 5
2	AS	CCV 1	AV	ATR 5
3	AS	WVF 5	AS	R 1
4	AV	WVF 3	AS	ATR 1
5	RS	WVF 5	RV	R 3
6	RS	ATR 1	RV	WVF 3
7	RV	WVF 5	RS	CCV 3
8	RV	HV 1	RS	ATR 3

Digging Deeper With the Three Best-Performing Long and Short Filters

A closer look at the three best performing long filters demonstrates their different behaviours. WVF 5 AV is the only algorithm with a 12-month information ratio more often positive than not and on average north of zero. Moreover, its information ratio oscillates around zero and tends to stay in positive or negative territory.[10] A system-switching trader could thus benefit from altering between filtered and unfiltered systems. The bulk of excess return comes during losing months of the unfiltered strategy and have slightly negative average 12-month serial correlation. The two other filters both have a negative average information ratio heavily affected by a through beneath -1 during the simulation, as revealed by WVF 5 AS that outperforms the unfiltered system half the time. CCV 1 AS is most influenced by the market and unfiltered system returns. The important CCV decrease is beneficial in falling markets, but not enough to offset the lost performance in rising markets.

Table 7. Three best long filters: information ratio compared to unfiltered system, monthly excess return, and serial correlation analysis

	Filter	AV WVF 5	AS CCV 1	AS WVF 5
Information Ratio (IR)	% Positive IR	52.10%	35.29%	43.70%
	Average IR	0.03	-0.12	-0.12
Excess Return (ER)	% Positive ER	57.69%	40.77%	50.00%
	% Positive ER when Positive Unfiltered Monthly Return	48.78%	23.17%	46.34%
	% Positive ER when Negative Unfiltered Monthly Return	72.92%	70.83%	56.25%
	% Positive ER when Positive Russell 3000 Monthly Return	54.76%	32.14%	51.19%
	% Positive ER when Negative Russell 3000 Monthly Return	63.04%	56.52%	47.83%
Serial Correlation Excess Return	Mean 12-Month Serial Correlation	-0.07	-0.11	-0.04

The cumulative distribution functions of the four long systems clarify the filter effects on entry signals. Although win rates do not vary more than 2%, WVF 5 AV has fatter tails than its three counterparts and manages more winners above 3%. Interestingly, CCV 1 AS replicates the best filter better than WVF 5 AS: The CCV usage favours fatter tails and more losers below 3%, decreases the win percentage by 1%, and slightly improves the percentage winners above 3%. WVF 5 AS has almost the same cumulative distribution as the unfiltered system and only reduces trading by 3.91%.

Figure 4. Long systems: cumulative distribution function of trade profits

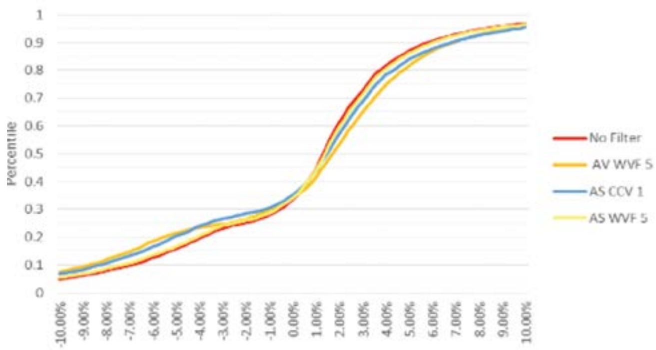


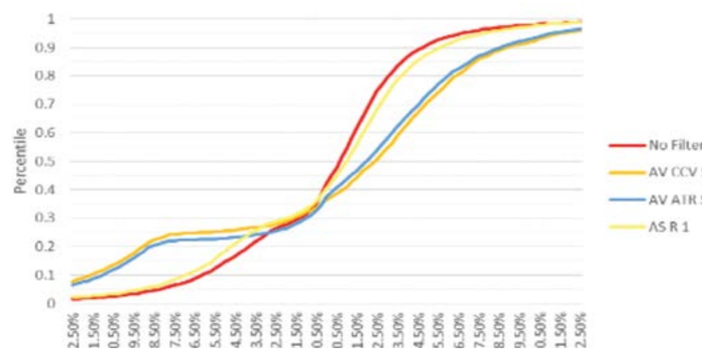
Table 8. Three best short filters: information ratio compared to unfiltered system, monthly excess return, and serial correlation analysis

	Filter	AV CCV 5	AV ATR 5	AS R 1
Information Ratio (IR)	% Positive IR	79.83%	82.35%	62.18%
	Average IR	0.25	0.27	0.08
Excess Return (ER)	% Positive ER	62.31%	60.77%	53.08%
	% Positive ER when Positive Unfiltered Monthly Return	50.88%	49.12%	38.60%
	% Positive ER when Negative Unfiltered Monthly Return	71.23%	69.86%	64.38%
	% Positive ER when Positive Russell 3000 Monthly Return	59.52%	64.29%	54.76%
	% Positive ER when Negative Russell 3000 Monthly Return	67.39%	54.35%	50.00%
Serial Correlation Excess Return	Mean 12-Month Serial Correlation	-0.01	-0.10	-0.09

The three short system filters manage positive information ratios more often, as well as higher averages. High CCV and ATR AV results approximate each other well for excess return in relation with the unfiltered system performance but differ when taking the Russell 3000 monthly move into account: CCV works better in bearish circumstances, while ATR prefers bullish environments. ATR manages the best average positive (3.41%) and negative (-2.75%) excess returns, but these are dampened by the lower frequency of positive excess returns. R 1 AS underperforms in every statistic and only briefly managed the best information ratio. The three indicators' average 12-month serial correlation is again close to 0.

Three key observations can be made from Figure 5. First, AS R 1 does not discriminate signals as much as the two other filters. Its cumulative distribution function is almost similar to the unfiltered system with heavier tails. Second, high AV CCV and ATR also have look-alike distributions: both improve the win rate and have more important losses. However, ATR has a slightly higher win rate than CCV and less volatile results: 16.7% (8.1%) of trades lose (win) more than 10% for CCV, whereas ATR only has 15.0% (7.1%). Third, the three filters increase the risk of a single trade. The fifth percentile of the distributions are -8.30, -14.04%, -13.67%, and -9.23% for the unfiltered, CCV, ATR, and R systems, respectively.

Figure 5. Short systems: cumulative distribution function of trade profits



Pushing Filter Boundaries or Combining Volatility Indicators

Tests show that filters can improve the original system and that systems benefit more from combining the right filters rather than using stricter limits for a single volatility indicator. On the one hand, the well-performing unfiltered long system ranks sixth overall, which is a fairly good result considering the amount of filtered systems tested. Moreover, it also manages a better recovery ratio than the multiple filter systems. On the other hand, the only two systems that consistently manage to beat the unfiltered system are WVF 65th and 70th percentile boundaries, and these two only reduced trading marginally. Remarkably, the best one-filter systems are obtained by loosening the filter criteria rather than pushing the boundaries further. Using the highest vigintile slightly improves CCV AS results but is harmful for WVF systems; the WVF 95 AS even loses money during the simulation. The three best two-filter systems use a lower quantile ATR RS and consistently reduce trading. Combining a high WVF AS and a low ATR RS results in the poorest performance. The combination of WVF 5 AV and ATR 1 RS halves the system exposure, increases (although not significantly) mean profit and risk reward and decreases ADD to 62.09% of the unfiltered system.

Table 9. Long. Three best two-filter systems vs. best limit one-filter systems (*not significant at 10% Welch T-Stat,[1] equal overall ank but better risk adjusted return than av wvf65)*

		Two-Filter System			Different Vigintile Boundary		
Key Metric/ System	No Filter	AV WVF 5 RS ATR 1	AS CCV 1 RS ATR 1	AS WVF 5 RS ATR 1	AV WVF65	AV WVF70	AS CCV25
Kelly	5	1	2	7	3	4	6
D3	7	2	1	6	4	5	3
Risk-Reward	6	5	2	7	3	4	1
Recovery Factor	4	5	7	6	1	2	3
ADD	7	2	1	5	4	6	3
Welch T-Stat	6	1	2	7	4	5	3
Overall	6	2	1	7	4	5	3[1]

Results are even more pronounced for the short system, as shown by Table 10; the three two-filter systems outperform single indicator systems in every key metric, with the exception of risk-reward. CCV 75 AV has the relatively highest exposure at 60% of the unfiltered system and differs with ATR 85 AV that benefits from stricter rules. An important R AS fall reduces both potential trade reward and risk. The ATR 5 AV and R 1 AS combination does not have the largest mean profit per trade but manages the best T-stat, as its trades are less variable. By contrast, the system with two ATR filters scores the highest average profit per trade but has more variability than its two counterparts.

Table 10. Short: three best two-filter systems vs. best limit one-filter systems *(1 mean profit increase significant at 1% 2 mean profit increase significant at 5%)*

		Two-Filter System			Different Vigintile Boundary		
Key Metric/ System	No Filter	AV CCV 5 AS R 1	AV ATR 5 AS R 1	AV ATR 5 RS ATR 1	AV ATR85	AS R05	AV CCV75
Kelly	7	2	3	1	5	4	6
D3	7	2	3	1	5	4	6
Risk-Reward	7	4	3	2	5	6	1
Recovery Factor	7	2	3	1	4	6	5
ADD	7	2	3	1	6	4	5
Welch T-Stat	7	21	11	31	41	62	51
Overall	7	2	3	1	5	6	4

Robustness

Using different datasets to verify the quality of best single- and two-filter systems provides mixed results that differ for long and short systems.

The long CCV-ATR combination, which is the best system between 2004 and 2014, underperforms on every other dataset. WVF 5 AV with ATR 1 RS works better than WTF 5 AS, as long as the considered stocks are not solely delisted. CCV on a stand-alone basis is not as performing as on the original dataset either. In addition, single WVF systems perform best for delisted securities and in earlier periods, as multiple indicators filtered more signals while being unable to avoid the 1987 and 2000 losing signals.

Table 11. Overall ranking of the best long single- and two-filter systems using different datasets

	No Filter	AV WVF 5 RS ATR 1	AS CCV 1 RS ATR 1	AS WVF 5 RS ATR 1	AV WVF65	AV WVF70	AS CCV25
Listed & Delisted 2004–2014	6	2	1	7	4	5	3
Listed & Delisted 1985–2003	3	5	7	6	1	2	4
Russell 3000 (11-2014 Constituents) 1985–2014	2	1	5	6	3	5	7
S&P 500 (11-2014 Constituents) 1985–2014	4	1	6	2	5	3	7
Delisted 1985–2014	3	5	7	4	1	2	6

Volatility filters for the short system have been more consistent. The ATR 5 AV and 1 RS has worked consistently with the exception of delisted securities, showing its higher efficiency to avoid losing trades in a winning environment, but lower capacity in falling markets. CCV-based systems again underperform compared to the original simulation, and extremely low R AS are relatively better on new datasets.

Table 12. Overall ranking of the best short single- and two-filter systems using different datasets

	No Filter	AV CCV 5 AS R 1	AV ATR 5 AS R 1	AV ATR 5 RS ATR 1	AV ATR85	AS R05	AV CCV75
Listed & Delisted 2004–2014	7	2	3	1	5	6	4
Listed & Delisted 1985–2003	7	5	3	1	6	2	4
Russell 3000 (11-2014 Constituents) 1985–2014	7	4	2	1	6	3	5
S&P 500 (11-2014 Constituents) 1985–2014	7	5	2	1	3	4	6
Delisted 1985–2014	7	2	1	4	6	3	5

Conclusion

This paper analyses five volatility measures (Average True Range, Historical Volatility, Candlestick Chart Volatility, Range, and Williams' VIX Fix) in conjunction with a high probability mean reversal system to gain insight on the filters' relative utility, on their behavioural differences in up and down markets, and on the advantages of combining or changing indicator limits. Six key metrics of relative rankings of filtered and unfiltered systems try to answer these questions.

First, the long unfiltered system works well during the simulation and is rarely improved by volatility filters.

Conversely, the short unfiltered system does not manage profits over the period and benefits greatly from volatility filtering.

Secondly, the most-rewarding and only worthy single indicator filter for bullish reversals is a high value of Williams' VIX Fix. The results agree with Gerald Appel's VIX interpretation: "Buy when there are high levels of VIX, which imply broad pessimism". The filter works particularly well on samples that include delisted stocks, helps increase average trade profit, and prefers lower requirements: leaner systems react better in the aftermath of the dotcom bubble, and the highest vigintile limit produces a losing system between 2004 and 2014. All is not rosy though; a high value is also benefitting the short system. These findings suggest that filtering with Williams' VIX Fix can lead to missing trades in a majorly bullish market, as well as entering stocks poised to go lower.

The story is completely different when solely considering the downside, as many filters improve results. Investors should especially look for high absolute average true range and candlestick chart volatility, which are both catastrophic for long reversals, and extremely low absolute slopes of range. High candlestick chart volatility works extremely well when the market is down and has fatter tails than its counterparts in its trade distribution, but does not work as well on earlier and smaller datasets. Results imply a low position sizing when using high candlestick chart volatility or average true range.

Historical volatility, at least with the tested parameters, finds itself on the other end of the indicator quality spectrum. This is both the case for long and short systems and therefore, by taking historical volatility as a proxy for standard deviation, confirms Marci's findings, "ATR seems to outperform standard deviation in many circumstances."

Using the five algorithms in absolute terms often results in better performance than relying on the indicators' relative 60-day value and slope. Only average true range slope and range value in long systems and relative candlestick chart volatility slope in short systems perform better relatively than absolutely.

Thirdly, combining indicators seems superior to stricter single indicators at first sight. This finding is consistently verified for short trades: Joining high absolute values of average true range with low relative slopes of the same indicator or low absolute slopes of range consistently achieve worthy results. The former combination is only beaten when exclusively considering delisted stocks and bears less profit than other combinations, and especially single indicator filters, during bubble bursts.

Nevertheless, combinations for long systems are often beaten by single indicator filters. An important example of this phenomenon happens during the 1985–2003 simulations: Not only do single William's VIX Fix systems profit eight times more than the best combinations, but they also perform better and recover faster than multiple filter systems. In view of the results and Howard Bandy's equation "System = model + data", multiplying the filters is best when going against the broad market and desynchronises faster with changing data.

Further volatility filter research could go multiple ways. On the one hand, researchers could investigate the findings with different mean reversion or trend-following systems and additional data. A broad database of Japanese stocks could be particularly interesting, as their market has mainly been falling since the 1980s. On the other hand, studies could look at volatility combined with seasonal and long-term filters.

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Notes

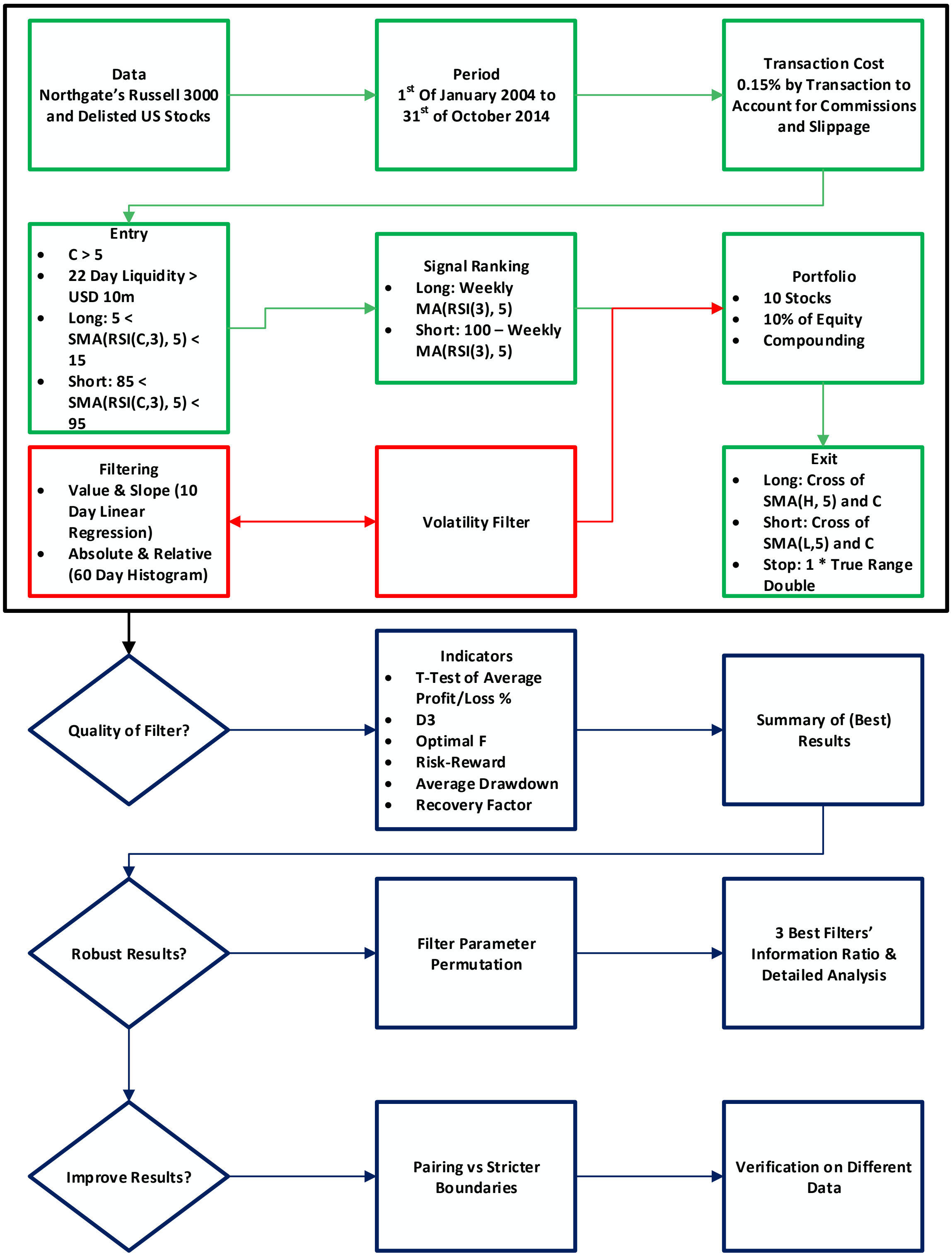
1. Billington (2014)
2. Stridsman (2000)
3. Fitschen (2013)
4. Kaufman (2013)
5. Hayashi (2013)
6. Williams (2007)
7. Kase (2005)
8. Walton (2014)
9. See Appendix 1: Methodology Outline
10. See Appendices 2 and 3: 12-month Information Ratios
11. Marci (2012)
12. Bandy (2011)

List of Abbreviations

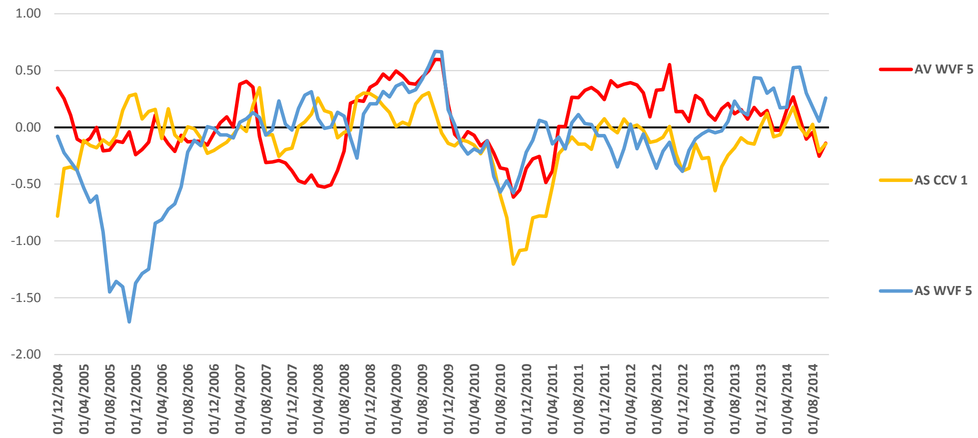
ADD — Average Drawdown
AS — Absolute Slope
ATR — Average True Range
AV — Absolute Value
CCV — Candlestick Chart Volatility
HV — Historical Volatility
MA — Moving Average
R — Range
RS — Relative Slope
RSI — Relative Strength Index
RV — Relative Value
SD — Standard Deviation
SMA — Simple Moving Average
TRD — True Range Double
WVF — Williams V

Appendices

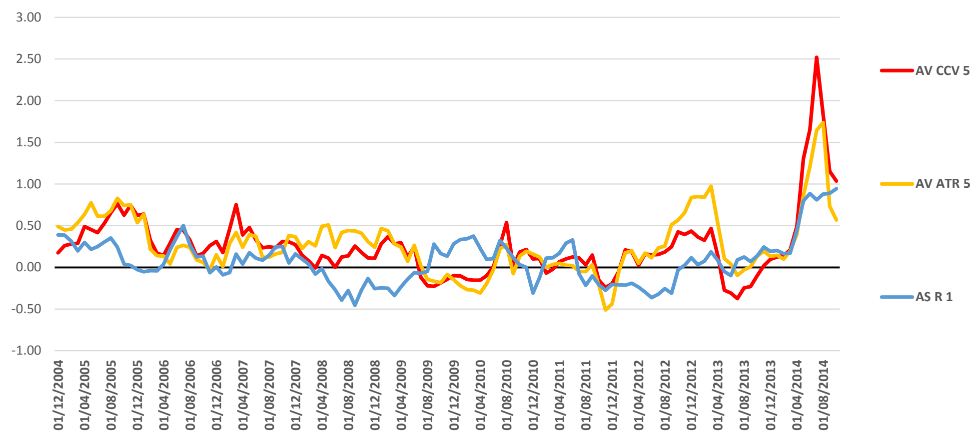
Appendix 1. Methodology Outline



Appendix 2. Rolling 12-Month Information Ratio for the Three Best Filters in the Long System



Appendix 3. Rolling 12-Month Information Ratio for the Three Best Filters in the Short System



Appendix 4. Indicators Value and Slope Correlation: 100-Day Average (below) and Median (above) for the Jan 2004—Oct 2014 Period on the S&P 500, Russell 3000, and Nasdaq 100

		Value					**Slope**				
		ATR	HV	CCV	R	VF	ATR	HV	CCV	R	VF
Value	ATR		0.84	0.87	0.47	0.56	0.46	0.48	0.55	0.16	-0.08
	HV	0.81		0.83	0.54	0.39	0.07	0.44	0.30	0.16	-0.20
	CCV	0.84	0.76		0.58	0.40	0.02	0.18	0.39	0.12	-0.20
	R	0.45	0.52	0.53		0.35	-0.09	0.11	0.16	0.56	-0.01
	VF	0.54	0.37	0.39	0.31		0.54	0.44	0.56	0.33	0.56
Slope	ATR	0.43	0.07	0.03	-0.05	0.50		0.62	0.65	0.07	0.33
	HV	0.44	0.41	0.19	0.08	0.43	0.60		0.71	0.29	0.15
	CCV	0.51	0.29	0.35	0.14	0.51	0.64	0.64		0.32	0.23
	R	0.14	0.18	0.11	0.55	0.29	0.13	0.27	0.28		0.32
	VF	-0.08	-0.17	-0.18	0.02	0.55	0.33	0.15	0.20	0.30	

Appendix 5. Unfiltered Long and Short Systems

	Long without Filter	**Short without Filter**
Annual Return %	11.08%	-5.30%
Risk Adjusted Return %	13.18%	-5.98%
All trades	5067	4723
Avg. Profit/Loss %	0.29%	-0.09%
Winners	66.39%	57.80%
Recovery Factor	2.29	-0.86
Risk-Reward Ratio	0.41	0
Optimal F	7.2484	-4.0363
D3	1.1301	-0.2348
ADD	-11.6761	-25.5101

Momentum of Relative Strength (MoRS): An Additional Tool for Relative Strength Investors

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Abstract

Relative strength in various forms is commonly utilized in a cross-market rank and rotation format. Yet the MoRS indicator is presented as an additional tool that provides the ability to measure acceleration and deceleration of relative strength between two securities in a more precise manner. MoRS can facilitate the timing of entries and exits and also offers a targeted approach to dynamic asset allocation and portfolio construction. Moving Average Convergence Divergence (MACD) offers the ability to measure momentum and trend in one indicator. MACD expressed as a ratio standardizes the distance between two moving averages and enables comparative analysis between two or more securities. MoRS replaces price with price divided the S&P 500 in a MACD ratio construct. Consequently, MoRS offers the opportunity to measure when relative strength leaders are beginning to lag and conversely when relative strength laggards are beginning to lead. The utility of MoRS is demonstrated in a Russell 2000 versus S&P 500 switching strategy, Sector ETF portfolios as well as a sector ETF and individual stock buy signal. It is expected that this study will be appealing to financial advisors, portfolio managers and analysts, and traders who are interested in utilizing a unique indicator that offers additional ways to utilize relative strength in a variety of targeted applications.

Introduction

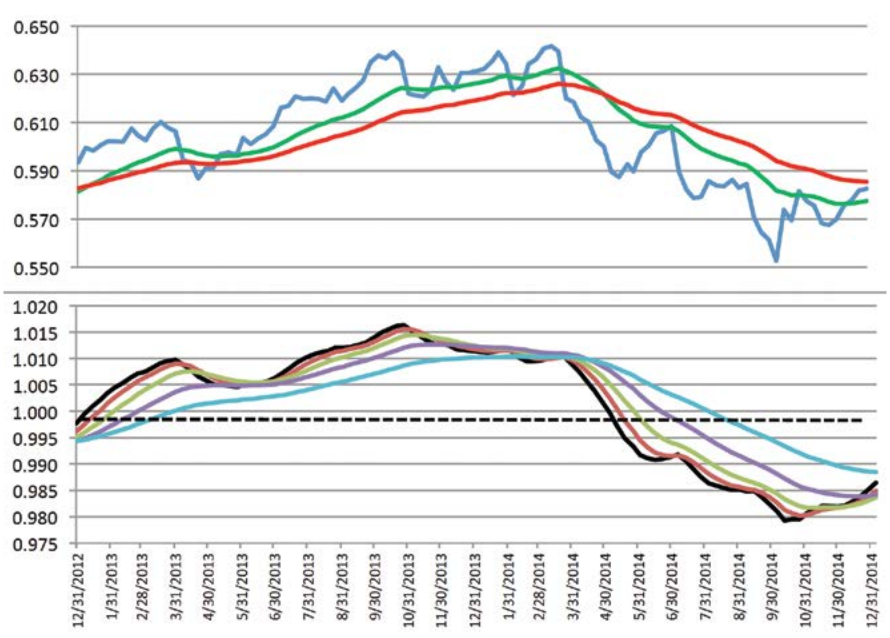
Analysts are pressed to recommend their best ideas, while portfolio managers are expected to select securities that will outperform. Relative strength in various forms offers the ability to identify and rank relative strength leaders across a universe of securities, yet few relative strength methods offer the ability to measure in a more precise manner when relative strength leaders are beginning to lag or when relative strength laggards are beginning to lead. By substituting price with price divided by an index, MoRS (Momentum of Relative Strength) converts a Moving Average Convergence Divergence (MACD) ratio into an indicator that measures acceleration and deceleration of relative strength. Consequently, from a relative strength standpoint, MoRS offers a more precise way to determine when to buy a relative strength laggard or sell a relative strength leader. Additionally, MoRS offers the opportunity to develop targeted approaches to dynamic asset allocation and portfolio construction.

Background of Relevant Indicators

MACD was developed by Gerald Appel in the late 1970s. MACD utilizes moving averages to measure trends, and by subtracting a longer term moving average by a shorter term moving average, it also measures momentum (Appel, 2005).

MoCS (Momentum of Comparative Relative Strength), developed by Christopher Hendrix, CMT, is an indicator identical to MACD with the exception that price is replaced by price divided by an index, sector, or other security (Carr, 2008, p 70–71).

Figure 1. RS ratio and 19- and 39-week EMAs (top window), MoRS ratio and 4-, 9-, 19- and 39-week EMAs (bottom window)



Materials and Methods

Calculation of MoRS

The Russell 2000 (RUT) and S&P 500 index (SPX) are utilized to provide an example of the calculation of MoRS. For purposes of this study, 19- and 39-week exponential moving averages (EMAs) are selected as the short and longer term moving average lengths, respectively. The steps in calculating MoRS include:

Step 1: Create the relative strength (RS) ratio line. This is done by dividing the weekly price of RUT by the weekly price of SPX. (Blue line in top window of Figure 1)

Step 2: Create 19- and 39-week EMA of the RS ratio line. (Red and green lines in top window Figure 1)

Step 3: Create the MoRS ratio by dividing the 19-week EMA of the RS ratio line by the 39-week EMA of the RS ratio line. (Black line in bottom window of Figure 1)

Step 4: Calculate 4-, 9-, 19- and 39-week EMA signal lines of the MoRS ratio. (Bottom of Figure 1)

The top window of Figure 1 allows us to view the relative strength trend of RUT versus SPX. When the 19-week EMA crosses above the 39-week EMA, the relative strength trend is positive. When the 19-week EMA crosses below the 39-week EMA, the relative strength trend of RUT versus SPX is negative. 19- and 39-week EMA crossovers result in the MoRS ratio crossing above and below the 1.0 level, which can be viewed in the bottom window of Figure 1. Additionally, the bottom window in Figure 1 allows us to view the momentum of relative strength between RUT and SPX. When the MoRS ratio (black line) is trending upward, the relative strength of RUT versus SPX is accelerating. Conversely, when the MoRS ratio is trending downward, the relative strength is decelerating. Notice in the top window of Figure 1, the RS ratio began to trade sideways in late 2013 and early 2014. This was a sign of waning momentum of relative strength. The identification of this development was more evident by viewing the October 2013 MoRS ratio peak and subsequent downturn in momentum, which preceded the RS ratio line peak. The 4-, 9-, 19- and 39-week EMA signal lines (red, green, blue and purple) offer the opportunity to assess the relative attractiveness of RUT versus SPX over various timeframes. The Appendix illustrates in more detail the steps in calculating the RS line and MoRS ratio.

Alternative Calculation of MoRS

A secondary contribution is the fact that MoRS can be approximately derived by dividing the MACD ratio of one security by another. The 19- and 39-week MACD ratios of RUT and SPX are depicted in Figure 2. A MACD ratio is created by dividing rather than subtracting the short-term moving average by the longer term moving average. This standardizes the distance between the two by expressing this difference as a ratio. MACD ratio crosses above and below 1.0 are identical to MACD crosses above and below 0. MACD ratios can facilitate comparative analysis of momentum and trend by assessing the slope and level of one security versus another. Yet, if MoRS can be derived by dividing the MACD ratio of one security by another, then MACD ratios can also facilitate the comparative analysis of momentum and trend of relative strength. This analysis is made easier by converting the MACD ratios into MoRS by dividing the MACD ratio of one security by another.

Multiple Signal Line Approach

Buying and selling a security based on a signal line crossover is a common approach. The idea is to capture the sweet spot or momentum in a trend. Yet, these strategies can be prone to whipsaw trades and may also cut profits short. Conversely, a decision can be made to buy on a signal line crossover and to hold a security when the indicator is above 1.0. This offers the ability to let winners run. But selling after MoRS has crossed below the 1.0 line may result in a sale that occurs after a substantial decline from a peak. A multiple signal line approach is introduced and tested against a traditional signal line approach. It is expected that a MoRS multiple signal line approach will reduce whipsaw trades and also deliver better returns as a result of allowing relative strength winners to run. These scenarios are identified in the boxes located in Figure 2. Essentially a multiple signal line approach offers profit opportunity across various momentum of relative strength timeframes.

For purposes of this study, a 19 39 MoRS and 9-week EMA crossover will be compared against a MoRS multiple signal line approach. The rules of the crossover and the multiple signal line approach are outlined in Table 1. There are two distinctions between each of these. Rule set 2 waits until the 4 EMA signal line crosses above the 9 EMA signal line, whereas rule set 1 buys when the MoRS ratio crosses above the 9 EMA signal line. This is a minor distinction, yet it is expected that rule set 2 will result in fewer whipsaw trades. The second distinction is that rule set 1 sells when the MoRS ratio crosses below the 9 signal line, whereas rule set 2 does not signal a sell until the 4 EMA signal line crosses below the 39 EMA signal line.

Figure 2. 19 39 MACD ratio of RUT and SPX, MoRS and derivation of MoRS

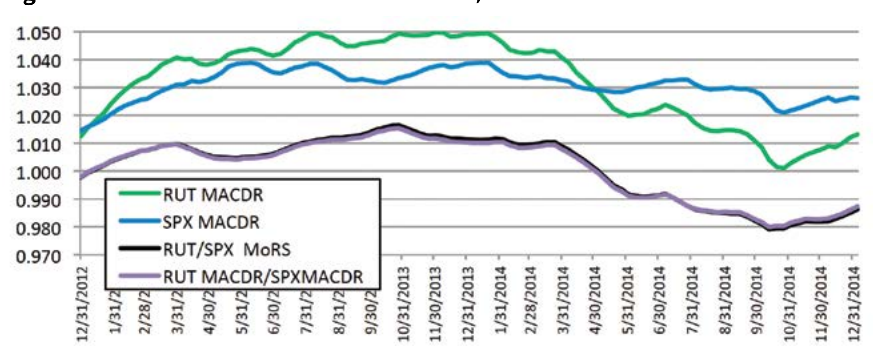


Figure 3. RUT/SPX MoRS multiple signal lines and whipsaw periods

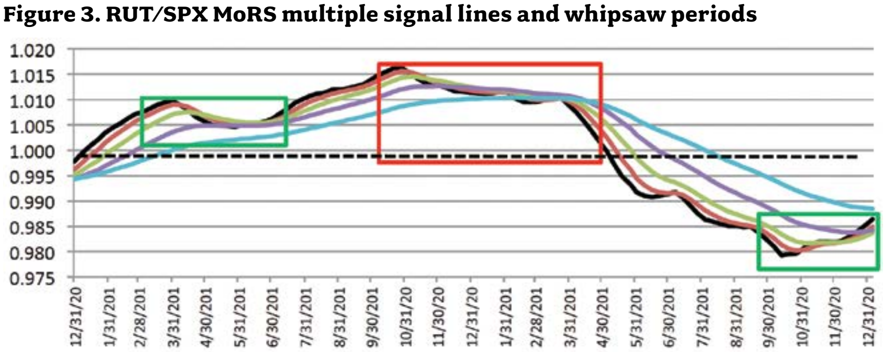


Table 1. Trading rules

Rule set 1 = MoRS 9 crossover = Buy security when MoRS is > 9 EMA signal line, Sell when MoRS is < 9 EMA signal.
Rule set 1 = MoRS 4,9,19,39 = Buy security when MoRS 4 EMA signal line is > 9 or 19 or 39 EMA signal line, Sell when MoRS 4 EMA is < 39 EMA signal line

Results

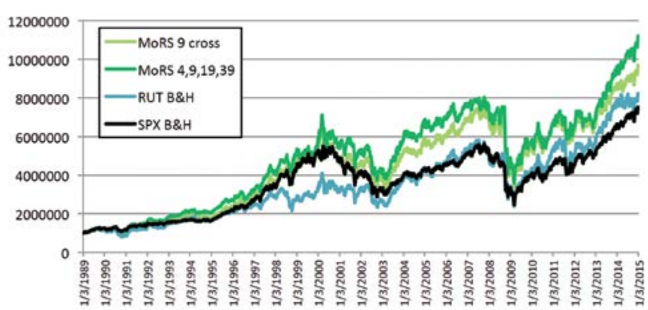
Russell 2000 and S&P 500 Switching Strategy

The 19 39 MoRS ratio indicator is applied to the Russell 2000 and S&P 500. When MoRS is positive the strategy buys RUT, and when MoRS turns negative, the strategy buys SPX. In Table 2 it can be seen that rule set 2 outperformed rule set 1 and also resulted in fewer total trades. Both rule sets outperformed the buy and hold returns of the Russell 2000 and S&P 500.

Table 2. RUT versus SPX switching strategy returns, volatility and number of trades

Rule Set	MoRS 9 cross	MoRS 4,9,19,39	RUT B&H	SPX B&H
Total Return	857.96%	1005.98%	713.46%	641.11%
Avg. Annual '89-'14	10.81%	11.43%	10.17%	9.54%
Annualized	9.08%	9.68%	8.40%	8.01%
Std. Dev. '89-'14	18.96%	19.17%	19.37%	17.50%
Coeff. Of Variation	1.75	1.68	190.51%	183.46%
Max Drawdown	-49.25%	-45.96%	-42.37%	-45.83%
# of trades (round trip)	77	56		

Figure 4. Equity curves of the RUT versus SPX switching strategy



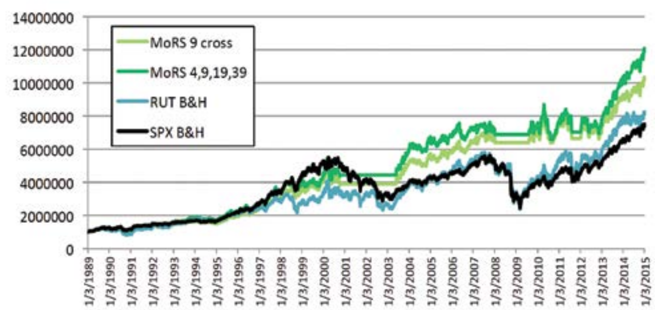
RUT and SPX Switching Strategy With SPX Long-Term Trend

In this strategy test, a long-term trend filter, and a rule is added that the strategy will only trade if the long-term trend of the S&P 500 is positive (9 week EMA > 39 Week EMA). Conversely, if the long-term trend of SPX is negative (9-week EMA < 39-week EMA), the strategy does not trade or sells the current position and defaults to cash or a money market fund (MMF). As can be seen in Table 3 and Figure 4, this strategy yielded similar returns and the draw down was reduced to 20%.

Table 3. RUT/SPX switching strategy with SPX long-term trend filter

Rule set	MoRS 9 cross	MoRS 4,9,19,39	RUT B&H	SPX B&H
Total Return	921.22%	1091.52%	713.46%	641.11%
Avg. Annual '89-'14	10.24%	10.91%	10.17%	9.54%
Annualized	9.35%	10.00%	8.40%	8.01%
Std. Dev. '89-'14	14.17%	14.48%	19.37%	17.50%
Coeff. Of Variation	1.38	1.33	190.51%	183.46%
Max Drawdown	24.05%	20.55%	42.37%	45.83%
# of trades (round trip)	65	50		

Figure 5. RUT/SPX MoRS switching strategy with SPX long-term trend filter



S&P Sector ETF MoRS Ratios

The MoRS ratios in Figure 6 are the result of dividing the weekly price of each sector by the weekly price of the S&P 500 ETF SPY. Notice the MoRS ratio line of XLE trended higher into a June peak, which was followed by a sharp decline into the end of the year. Table 4 illustrates the 2014 first and second half performance of each sector ETF. XLE returned 14.36% in the first half of the year and outperformed SPY's return of 7.49%. Conversely, XLE lost 19.58% in the second half of 2014 and underperformed SPY's return of 5.98%. XLV's MoRS ratio bottomed on June 20 and continued to trend higher through the end of the year. In the second half of 2014, XLV gained 13.19% and outperformed SPY's return of 5.98%.

Figure 6. 2014 MoRS ratios of the 10 S&P Sector ETFs

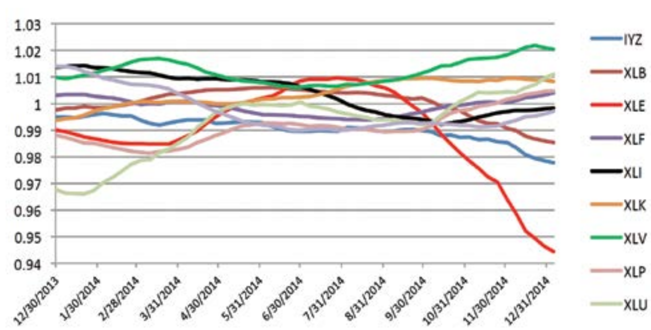


Table 4. 2014 first and second half total returns of S&P Sector ETFs

Dates/Symbol	IYZ	XLB	XLE	XLF	XLI	XLK	XLV	XLP	XLU	XLY	SPY
Jan.- June 2014	2.58%	8.40%	14.36%	5.23%	5.33%	8.73%	11.06%	5.48%	18.10%	1.39%	7.49%
July - Dec. 2014	-1.71%	-0.57%	-19.58%	9.67%	5.17%	8.66%	13.19%	9.74%	9.99%	8.09%	5.98%

Sector ETF Buy Signal

The objective of this test is to determine the utility of MoRS as a buy signal in an oversold relative strength condition. Three conditions must be present for the strategy to accept a buy signal: 1) 4-week EMA signal line crosses above the 9-week EMA signal line; 2) MoRS ratio value is below the 1.0 line; 3) Long-term trend of SPY is positive. A sell signal is triggered when the 4-week EMA signal line crosses below the 9-week EMA signal line, or after a position has been held for 26 consecutive weeks. As can be seen in Table 4, the Sector universe generated 101 trades, of which 65% were profitable. The average gain was 9.55% versus an average loss of -3.23%. Only 47.64% of the trades outperformed SPY. Yet, the average level of outperformance was 5.85% versus an average level of -3.80% of underperformance.

Table 5. Sector ETF MoRS 4 and 9 signal cross results

Trade Statistics	Sector	SPY	RS Trade Statistics	RS
Total Return	480.78%	425.49%	Total outperformance	55.29%
# of profitable trades	66	77	# of outperformers	46
# of unprofitable trades	35	24	# of underperformers	55
average gain	9.55%	7.04%	average outperformance	5.65%
average loss	-3.23%	-4.20%	average underperformance	-3.80%
win rate	65.48%	77.76%	win rate	47.64%

Figure 7 depicts the MoRS ratio and multiple signal lines of XLU in 2013–2014. The MoRS 4 and 9 signal line crossover triggered a buy of XLU on 2/10/2014 and a sale on 7/28/2014, yet at that time, the multiple signal line crossover would have continued to maintain a position.

Figure 7. MoRS of XLU and multiple signal lines

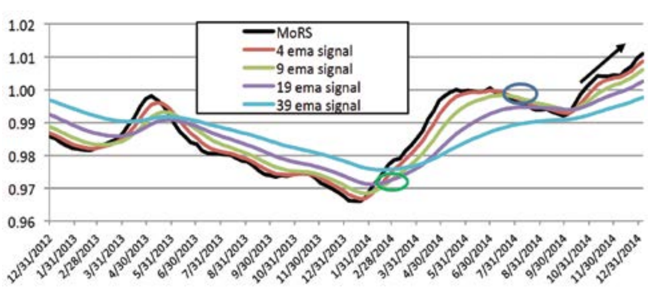
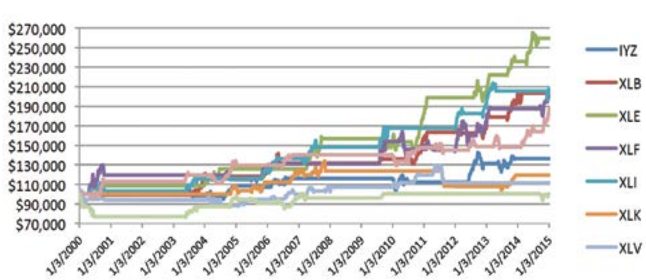


Figure 8. ETF equity curves, MoRS 4 and 9 signal cross buy



S&P Sector ETF Portfolios

Rule set 1 (MoRS and 9 signal line cross) is tested against rule set 2 (MoRS multiple signal line cross). Two sector portfolios are created for each of these rule sets, and both portfolios dedicate a position or sub strategy to each of the 10 S&P Sector ETFs. Additionally, each portfolio accepts signals only when the S&P 500 ETF is trading in a positive long-term trend. Each Sector ETF is purchased when a buy signal occurs. Yet when a sell signal occurs, the proceeds are parked in cash or a money market account. Each portfolio's exposure can vary between 100% invested (10% allocation to each ETF) and 0%. Essentially, the objective is to create a portfolio that offers a targeted yet dynamic approach to sector investing while also providing a degree of bear market protection. Table 5 and Figure 9 illustrate the results of each portfolio and show that the multiple signal line portfolio outperforms the MoRS and 9 signal crossover portfolio, while also resulting in fewer trades. "SPY if MoRS 4,9,19,39" assumes that money is invested into SPY instead of the MoRS multiple signal line portfolio. Consequently, the relative outperformance of the MoRS multiple signal portfolio can be directly measured. Additionally, the MoRS multiple signal portfolio outperformed the buy and hold results of the sector average and the S&P 500 ETF SPY.

Table 6. S&P Sector ETF portfolio results

Rule	MoRS 9 cross	MoRS 4,9,19,39	SPY 4,9,19,39	Sector B&H	SPY BH
Total Return	91.72%	140.86%	117.95%	132.93%	84.37%
Avg. Annual	4.54%	6.22%	5.55%	7.33%	5.95%
Annualized	4.43%	6.04%	5.33%	5.80%	4.16%
Std. Dev. '00-'12	4.94%	6.48%	6.95%	17.45%	18.99%
Coeff. of Variation	1.09	1.04	1.25	2.38	3.19
Max Drawdown	-5.78%	-8.56%	-10.95%	-48.61%	-51.32%
# of trades (RT)	391	300			

Figure 9. Equity curves of Sector portfolios compared to Sector composite and SPY

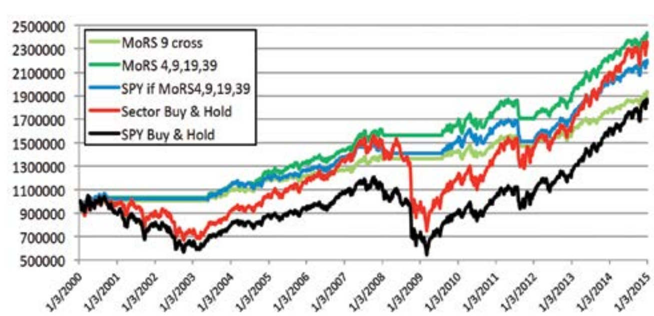
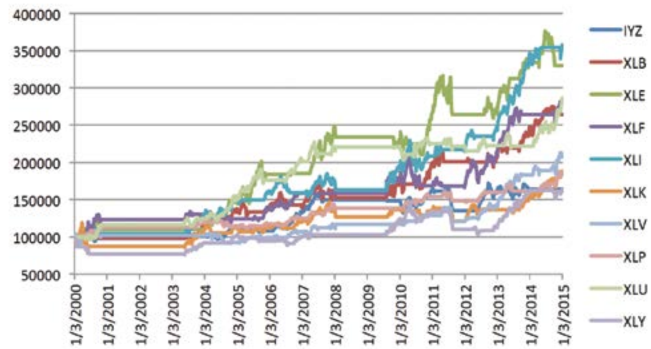


Table 7 illustrates the Sector ETF or money market holdings of the multiple signal line portfolio. Rather than competing against all sector ETFs, this portfolio construction allows each Sector ETF to compete only with SPY on a one-to-one basis and offers a targeted yet dynamic approach to sector investing.

Table 7. MoRS multiple signal line Sector ETF portfolio signals

Date	IYZ or MMF	XLB or MMF	XLE or MMF	XLF or MMF	XLI or MMF	XLK or MMF	XLV or MMF	XLP or MMF	XLU or MMF	XLY or MMF
6/30/2014	MMF	XLB	XLE	MMF	MMF	XLK	MMF	XLP	XLU	MMF
7/7/2014	MMF	XLB	XLE	MMF	MMF	XLK	MMF	XLP	XLU	MMF
7/14/2014	MMF	XLB	XLE	MMF	MMF	XLK	MMF	XLP	XLU	MMF
7/21/2014	MMF	XLB	XLE	MMF	MMF	XLK	MMF	XLP	XLU	MMF
7/28/2014	MMF	XLB	XLE	MMF	MMF	XLK	MMF	XLP	XLU	MMF
8/4/2014	MMF	XLB	XLE	MMF	MMF	XLK	MMF	XLP	XLU	MMF
8/11/2014	MMF	XLB	XLE	MMF	MMF	XLK	MMF	XLP	XLU	MMF
8/18/2014	MMF	XLB	XLE	MMF	MMF	XLK	MMF	XLP	XLU	MMF
8/25/2014	MMF	XLB	XLE	MMF	MMF	XLK	XLV	XLP	XLU	MMF
9/1/2014	MMF	XLB	XLE	MMF	MMF	XLK	XLV	MMF	XLU	XLY
9/8/2014	MMF	XLB	XLE	MMF	MMF	XLK	XLV	MMF	XLU	XLY
9/15/2014	MMF	XLB	XLE	XLF	MMF	XLK	XLV	MMF	XLU	XLY
9/22/2014	MMF	XLB	XLE	XLF	MMF	XLK	XLV	MMF	XLU	XLY
9/29/2014	MMF	XLB	XLE	XLF	MMF	XLK	XLV	MMF	XLU	XLY
10/6/2014	MMF	MMF	MMF	XLF	MMF	XLK	XLV	XLP	XLU	XLY
10/13/2014	MMF	MMF	MMF	XLF	MMF	XLK	XLV	XLP	XLU	XLY
10/20/2014	MMF	MMF	MMF	XLF	MMF	XLK	XLV	XLP	XLU	XLY
10/27/2014	MMF	MMF	MMF	XLF	MMF	XLK	XLV	XLP	XLU	XLY
11/3/2014	MMF	MMF	MMF	XLF	MMF	XLK	XLV	XLP	XLU	MMF
11/10/2014	MMF	MMF	MMF	XLF	MMF	XLK	XLV	XLP	XLU	MMF
11/17/2014	MMF	MMF	MMF	XLF	MMF	XLK	XLV	XLP	XLU	MMF
11/24/2014	MMF	MMF	MMF	XLF	XLI	XLK	XLV	XLP	XLU	MMF
12/1/2014	MMF	MMF	MMF	XLF	XLI	XLK	XLV	XLP	XLU	XLY

Figure 10. Equity curves of each Sector ETF in the MoRS multiple signal line portfolio



The multiple signal line portfolio outperformed all benchmarks. Looking at Table 8, it can be seen that there was a wide variation in performance between each of the 10 sector ETFs on a buy and hold basis over the past 15 years. XLE, XLP, and XLU were among the top performers, while the returns of IYZ, XLF, and XLK were bottom performers. Additionally, XLK and IYZ actually lost money on a buy and hold total return basis over the test period,while XLF generated a return of approximately one half of SPY's return.

In looking at Table 9, it can be seen that the sector multiple signal line portfolio on average was invested in S&P Sector ETFs only 41.70% of the time. Figure 10 depicts the individual sector ETF equity curves of the multiple signal line portfolio.

Table 8. SPY and Sector ETF buy and hold total returns '00-'14

Period	SPY	IYZ	XLB	XLE	XLF	XLI	XLK	XLV	XLP	XLU	XLY
'00-'14	84.37%	-22.72%	162.41%	276.38%	41.15%	149.05%	-9.77%	173.75%	191.79%	192.12%	175.18%

Table 9. Sector portfolio percentage of time invested

	Average	IYZ	XLB	XLE	XLF	XLI	XLK	XLV	XLP	XLU	XLY
# weeks	326.1	331	338	329	318	377	349	309	285	339	286
% exposure	41.70%	42.33%	43.22%	42.07%	40.66%	48.21%	44.63%	39.51%	36.45%	43.35%	36.57%

Table 10. Sector hierarchy

Sector Hierarchy Portfolio					
Hierarchy	**Position 1**	**Position 2**	**Position 3**	**Position 4**	**Position 5**
1	XLB	XLF	XLE	XLI	XLK
2	IYZ	XLU	XLY	XLV	XLP
3	MMF	MMF	MMF	MMF	MMF

Table 11. Sector hierarchy returns versus SPY

Risk and Reward	Sector Hierarchy	SPY if MoRS 4,9.19,39	SPY Buy and Hold
Total Return	**253.63%**	**181.21%**	**84.37%**
Avg. Annual	9.20%	7.54%	5.94%
Annualized	9.44%	7.66%	4.47%
Std. Dev. '01-'12	9.84%	9.65%	19.00%
Coeff. Of Variation	1.07	1.28	3.20
# of trades (RT)	326		

Sector Hierarchy Portfolio

The MoRS multiple signal line approach is applied to a hierarchy portfolio and is created with the intent of reducing the percentage of time that a portfolio is allocated to a money market position. The hierarchy reduces the number of positions or sub strategies from 10 to five by arranging five sub strategies based on a risk on and risk off mode. Table 10 outlines the order of the Sector ETF hierarchy. In Position 1, for example, if the MoRS signal on XLB is positive, the strategy either buys or holds XLB. If the MoRS signal on XLB changes to a sell, the strategy sells XLB and buys IYZ if the MoRS signal on IYZ is positive. If neither XLB or IYZ has a positive MoRS signal, the strategy owns a 20% money market position until either XLB or IYZ generates a new MoRS buy signal. Additionally the portfolio only accepts trades when the long-term trend of SPY is positive. On average, this portfolio maintained sector ETF exposure 62% of the time.

Figure 11. Sector hierarchy portfolio equity curve versus SPY

S&P 100 Stocks Buy Signal

The objective of this test is to assess the utility of MoRS as a buy signal in an oversold relative strength condition. The conditions are identical to the Sector buy signal, as three conditions must be present for the strategy to accept a buy signal: 1) 4-week EMA signal line crosses above the 9-week EMA signal line; 2) MoRS ratio value is below the 1.0 line; 3) long-term trend of SPY is positive. A sell signal is triggered when the 4-week EMA signal line crosses below the 9-week EMA signal line, or after the position has been held for 26 consecutive weeks. Table 12 shows that this signal generated 500 trades. 58% of these trades were profitable, and the average gain was 14.94% compared to an average loss of 6.55%. 44.80% of trades outperformed the S&P 500, and the average level of outperformance was 12.16% versus an average level of underperformance of -7.47%.

Table 12. S&P 100 stocks MoRS 4 and 9 signal cross results

Trade Statistics		RS Trade Statistics	
Total Return	2548.43%	Total outperformance	605.80%
# of profitable trades	290	# of outperformers	224
# of unprofitable trades	210	# of underperformers	276
Average Gain	14.94%	Average outperformer	12.16%
Average Loss	-6.55%	Average underperformer	-7.47%
% profitable	58.00%	% outperformance	44.80%

Figure 12. AMZN MoRS 4 and 9 signal lines

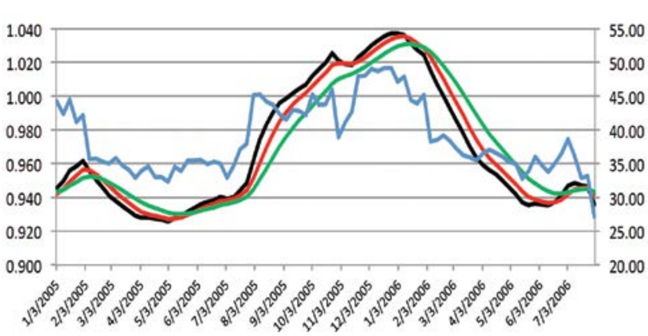


Figure 12 depicts the weekly price of Amazon in blue. While the MoRS buy signal in mid-2005 led to a profitable trade, the buy signal in July 2006 signaled a sell only three weeks later and resulted in a loss of -24.76%.

Discussion

The advantage of utilizing a multiple signal line approach with MoRS is evident when compared to trading off of one signal line, as the multiple signal line approach outperformed in the Russell 2000 versus S&P 500 test as well as the Sector ETF portfolios. Additionally, the multiple signal line approach generated fewer total trades. The results of the Sector ETF portfolios appear to demonstrate the utility of MoRS, particularly from a risk standpoint, as the first sector portfolio maintained approximately a 40% allocation to sector ETFs and a 60% allocation to cash. Similarly, the Sector Hierarchy portfolio on average maintained approximately a 60% allocation to sector ETFs and a 40% allocation to cash. Yet, in viewing the results from the Sector portfolio in Table 6, the margin of returns appears somewhat lacking. It is possible, of course, that in some cases the MoRS multiple signal line approach sold a relative strength winner too soon and held a loser too long. In looking at Table 8, it also possible that the available returns from the sector universe were somewhat lacking, as IYZ and XLK failed to generate a positive return, while the return from XLF was less than one half of the return of SPY.

Figure 6 illustrates the MoRS ratios of the 10 S&P Sector ETFs. This chart overlay provides a graphic depiction of relative strength winners and losers as well relative strength winners that began to lag and relative strength laggards that began to lead. As a result, it is evident that this chart construct can facilitate the simultaneous comparative analysis of a multitude of securities based on momentum of relative strength.

The MoRS 4 and 9 signal cross buy in the Sector ETF and S&P 100 stock universe provides evidence of the indicator's ability to detect when a relative strength laggard is beginning to lead. Yet by looking at XLU in Figure 7, it is probable that in many cases, the 4 and 9 signal line cross sells too soon. While a 4 and 39 signal cross sell was not tested, in the buy signal tests it is apparent in the Russell 2000 versus S&P 500 and Sector portfolio tests that utilizing a 4 and 39 signal cross sell allowed relative strength winners to run when compared to the MoRS and 9-week signal cross sell.

Conclusion

The utility of MoRS has been demonstrated as a buy signal and dynamic asset allocation tool. MoRS measures the momentum of relative strength on a one-to-one basis. This offers the opportunity to identify when relative strength winners are beginning to lag and when relative strength laggards are beginning to lead, and also offers the opportunity to develop targeted approaches to dynamic asset allocation. As a result, it is expected that this study will be appealing to financial advisors, portfolio managers, analysts, and traders.

Software and Data

All strategy tests were performed in Excel, a Microsoft product. Only 50 S&P 100 stocks were utilized in the S&P 100 study, as they were the only stocks that had a data history prior to the 01/03/2000 start date of the study based on price data downloaded from XLQ Plus. IYZ did not begin trading until May 2000. Signals, if any, were ignored until trading history resulted in an accurate MoRS calculation.

References

Appel, Gerald, 2005, Power Tools for Active Investors.

Carr, Mike, 2008, Smarter Investing in any Economy, p. 70—71

Appendix

Detailed Steps in Calculating the Rs Line

	19-Week EMA	39-Week EMA
Smoothing factor	2/(1+19) = .10	2/(1+39) = .05
Smoothing factor	1-.10 = .90	1-.05 = .95
RS line Week One	calculate 19 Week SMA	calculate 39 Week SMA
RS line Week Two	Current RS line x .10 + Last week RS line SMA x .90	Current RS line x .05 + Last week RS line SMA x .95
RS line Week Three	Current RS line x .10 + Last week RS line EMA x .90	Current RS line x .05 + Last week RS line EMA x .95

Detailed Steps in Calculating the MoRS Ratio

	4-Week EMA signal	9-Week EMA signal	19-Week EMA signal	39-Week EMA signal
Smoothing factor	2/(1+4) = .40	2/(1+9) = .20	2/(1+19) = .10	2/(1+39) = .05
Smoothing factor	1-.40 = .60	1-.20 = .80	1-.10 = .90	1-.05 = .95
MoRS Week One	calculate 4 Week SMA	calculate 9 Week SMA	calculate 19 Week SMA	calculate 39 Week SMA
MoRS Week Two	Current MoRS x .40 + Last week MoRS SMA x .60	Current MoRS x .20 + Last week MoRS SMA x .80	Current MoRS x .10 + Last week MoRS SMA x .90	Current MoRS x .05 + Last week MoRS SMA x .95
MoRS Week Three	MoRS x .40 + Last week MoRS EMA x .60	MoRS x .20 + Last week MoRS EMA x .80	MoRS x .10 + Last week MoRS EMA x .90	MoRS x .05 + Last week MoRS EMA x .95

The Technical Footprints of Dividends on Stock Prices and Their Subsequent Exploitation

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Abstract

Many strategies are used to take advantage of the dividends that companies pay to their stockholders. An example includes the buy and hold strategy, whilst another common strategy is often referred to as dividend stripping. This paper asserts that market participants who seek dividends in their investment strategy leave clues and signs. This hypothesis is discussed and investigated with the aim of confirming that these footprints do exist. The empirical analysis is based on the Top 40 companies (as by market capitalization) as listed on the Johannesburg Stock Exchange. Moreover, the paper then examines whether the exploitation of these market anomalies proves profitable.

Introduction

Dividends and Their Footprints

Dividends matter. They are one of the simplest ways to assess the financial health of a company. Typically, a company will, in its growth phase, retain its earnings and reinvest them into the business to grow organically or through acquisition. However, as the company establishes itself as a profitable entity, it will distribute a portion of its earnings to stockholders in the form of dividend payments.

Dividends are paid out of profits. Therefore, a company that is paying a dividend is a profitable company. Moreover, if a company has a steady history of paying a dividend over a number of years, that company must, at the end of the day, be making real money. It is all very well and good for a company to be generating a paper profit, but that profit cannot be distributed to its stockholders.

When a company pays a dividend, it indicates that, after all decisions regarding capital expenditure and investment have been made by management, it can still give something back to the stockholders. This is a tremendous statement by the company. It is an indication that it is in good shape and will be around for years to come. If the dividends increase yearly it follows that the company's earnings are growing too. It says that the business is generating enough profit to cover the growth plans of management and return an increasing amount to stockholders.

In essence, the ability to declare and pay dividends as well as to increase payouts over time are all measures of a company's health and the soundness of its fundamental structure. According to Investopedia, prior to the introduction of disclosure rules in the 1930s, the dividend was a key metric in assessing the financial health of a publicly listed company.

Considering the important role that dividends play in the functioning of commerce, and specifically in the buying and selling of stock, it is prudent to investigate whether these payments have an impact on stock prices and their momentum. If, in fact, this force is present, does it then leave a footprint? This paper asserts that such does exist and deems it necessary to investigate further whether these footprints are worth following for profit and gain. In other words, it addresses the exploitation of these footprints as well.

Assumptions Made

Neoclassical economics makes basic assumptions about the economic human, known as *homo economicus*. Despite the many shortcomings of these, one must understand that if these substantive assumptions were not made, it would be impossible to arrive at any of the interesting conclusions to the issues economists study. Assumptions about human behavior are an essential starting point for any economic argument, even if these assumptions fail occasionally.

Similarly, this paper makes some assumptions about investor behavior in terms of dividend payments by companies. In doing so, it allows for the drawing of important conclusions regarding the payment of dividends and their subsequent exploitation. These assumptions include:

1. Dividends are signals sent by companies to the market.
2. These tend to be regular and stable.
3. There are strategies to capitalize on the payment of dividends.
4. When a company disappoints with its dividend announcement, it is punished by the market.
5. Granville's OBV is an indicator that can be used to assess accumulation.

These assumptions are not made in isolation. They are discussed below, and a case is made for their sensical adoption.

Materials and Methods

Materials

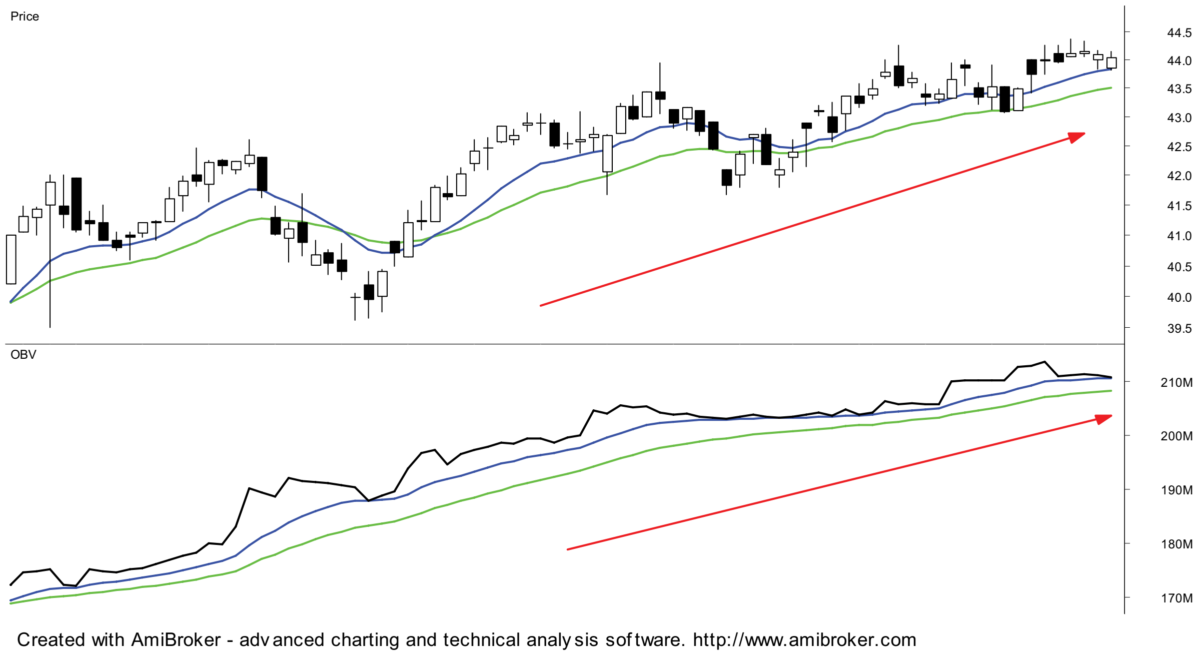
1. The charting platform used in testing for the footprints of dividends was Amibroker 5.80 Standard Edition.
2. JSE price and volume data was supplied by PDSNET (http://www.pdsnet.co.za).
3. Specifically, *ex*-dividend days of the current top 40 listed companies (as per market capitalization) were identified with the help of a spreadsheet, as provided to the author by the Johannesburg Stock Exchange. This covered the period from 5 January 2004 to 6 October 2014.
4. In particular, 628 *ex*-dividend dates were examined.

Methods

The MACDOBV Histogram

A unique indicator was devised for the testing of the footprints left by dividend seekers. The basic outline is detailed here but it is discussed further in Chapter 4. A MACD Histogram was derived for Granville's On Balance Volume (OBV) indicator (as opposed to price). As with price, so volume tends to trend, specifically as represented by OBV. (See Figure 1.)

Figure 1. EMAs may be plotted on price and OBV



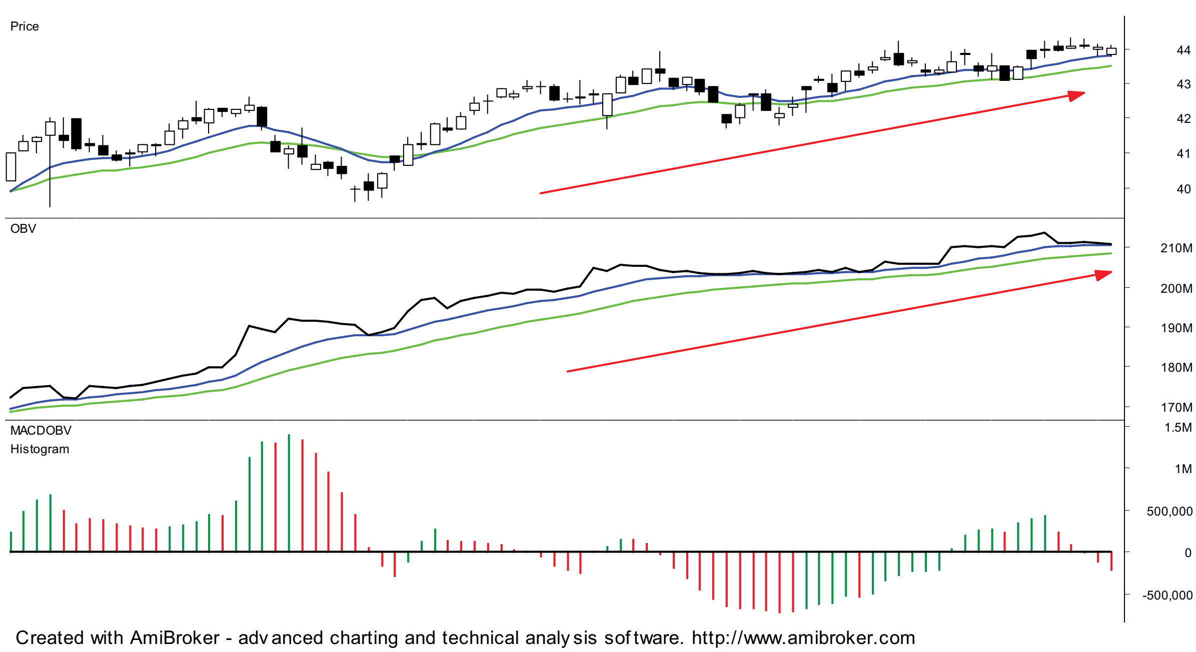
This figure shows price with a 12-day and 26-day exponential moving average (EMA). The bottom chart shows OBV (black) with the two EMAs. The EMAs make it easier to see that the trend is up (red arrows), with the shorter (blue) average above the longer (green) one.

The 12- ƒand 26- period EMAs are used to construct Gerald Appel's MACD indicator.[1] Thus, it follows that a MACD and its signal line can be constructed for OBV as well as for price.

To take this a step further. The MACD Histogram is an indicator derived from the MACD indicator. It tends to give earlier signals than the more lagging MACD. It is simply the difference between the MACD and the MACD signal line. This indicator can be applied to OBV:

Figure 2 is similar to Figure 1 except that it includes a third indicator—the MACD Histogram of OBV. This will be referenced to as the MACDOBV Histogram in the discussion that follows.

Figure 2. The MACD Histogram can be plotted for OBV as well



The *Ex*-dividend date

The *ex*-dividend date is the day when all stock of a particular company that is traded on that day no longer has any right to the most recent dividend declared. Existing stockholders will receive the dividend and the buyer will forgo that right. It makes the reconciliation of who is to be paid much simpler. On the *ex*-dividend date, the stock's price should fall by the amount roughly equal to the dividend amount per stock. Thus, when a stock trades *ex*-dividend, the demand for that stock will dry up by its dividend seekers. Therefore, this date is integral to the methodology in identifying the footprints of the dividend (or more specifically, the market participants demanding those dividends).

A Rules-Based approach

The hypothesis is that investors will purchase a stock leading up to the *ex*-dividend day and will purchase here with vigor. This being the case, there will be a certain momentum associated with this type of accumulation, which may be exploited for gain. To test this hypothesis, the approach will be rules-based. As such, the methodology imposes the following to determine if dividend payments (or more precisely the investors who are purchasing because of the dividend payments) indeed leave footprints in their wake:

1. The "cocking of the gun" is the *ex*-dividend date. This is of paramount importance, and the entire hypothesis rests on this rule. This dissertation is testing for the technical footprints of dividend payments. As such, its testing is intrinsically linked to the *ex*-dividend date.
2. A countback of 20 trading days from the *ex*-dividend date will be used to determine if accumulation of the stock in question is taking place. This approximates to a month prior to the stock going *ex*-dividend. This thesis will reference this day as the countback day.
3. The low of the countback day must be higher than the 200-day simple moving average. This is a simple means to eliminate stocks that are trending down from the universe of stocks to assess.
4. There must be two consecutive days of higher MACDOBV Histogram readings within five days from the countback day.[2] The reason for such a tight timeframe is the testing to see if investors are indeed accumulating with the required vigor. If they are, then this rule will make the footprints visible.
5. There must be no negative/bearish divergence between price and the MACDOBV Histogram.

If these conditions are met, an entry is triggered for the following day. However, there is further refinement of the rules to ensure that this investor vigor does not evaporate. The thesis views this vigor, or investor excitement, as the catalyst for the trail of footprints that can be followed and exploited for profit. It is an alternative method of catching the profitable momentum.

The refined rules include:

6. Given an entry, if the MACDOBV Histogram reading does not turn positive after a further three readings, an exit is signaled. The exit is imposed the following day.
7. If the MACDOBV Histogram starts off as or turns positive and then subsequently turns negative at any point, an exit is signaled. Again, this is enforced the following day.
8. The day before a stock goes *ex*-dividend is considered a mandatory exit. To be clear, the position is exited a day before the *ex*-dividend day.

Table 1. Capital allocations for 2004

T1cker	Ex-D1v1dend Date	Proift/Loss %	Profit/Loss	Cap1tal invested	Net Per Position	Cap1tal invested split	Total
NTC	2004-02-02	-6,36%	R -31,78	R 500,00	R 468,22		R468,22
AGL	2004-03-08	10,18%	R 23,83	R 234,11	R 257,95	Split over 2 positions	
SHP	2004-03-08	10,47%	R 24,50	R 234,11	R 258,61		R516,56
BVT	2004-03-15	4,29%	R 5,54	R 129,14	R 134,68	Split over 4 positions	
GRT	2004-03-15	-0,32%	R -0,42	R 129,14	R 128,72		
RMH	2004-03-19	-1,38%	R -1,78	R 129,14	R 127,36		
SLM	2004-04-19	12,36%	R 15,96	R 129,14	R 145,10		R535,87
MDC	2004-06-21	0,56%	R 0,60	R 107,17	R 107,77	Split over 5 positions	
MPC	2004-06-21	7,75%	R 8,31	R 107,17	R 115,48		
MTN	2004-06-28	-8,20%	R -8,78	R 107,17	R 98,39		
SAB	2004-07-05	-1,19%	R -1,27	R 107,17	R 105,90		
TBS	2004-07-05	-1,91%	R -2,05	R 107,17	R 105,12		R 532,67
Bll	2004-08-30	11,14%	R 19,78	R 177,56	R 197,34	Split over 3 positions	
SBK	2004-09-06	6,73%	R 11,95	R 177,56	R 189,50		
BVT	2004-09-13	6,70%	R 11,89	R 177,56	R 189,45		R 576,29
RMH	2004-10-18	3,04%	R 8,76	R 288,14	R 296,90	Split over 2 positions	
APN	2004-10-25	3,09%	R 8,91	R 288,14	R 297,05		R593,95
SAB	2004-11-29	0,47%	R 1,41	R 296,98	R 298,39	Split over 2 positions	
MPC	2004-12-06	0,47%	R 1,38	R 296,98	R 298,36		R596,74

Results

Testing for the Footprints

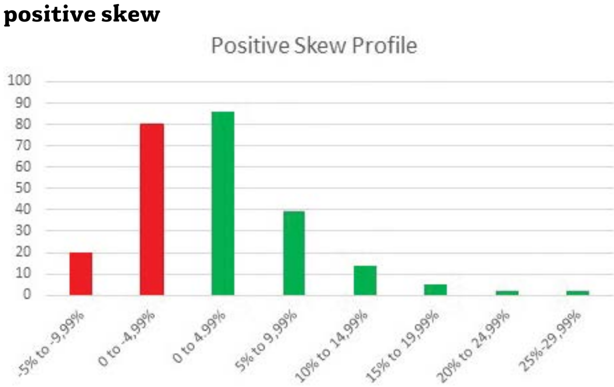
In testing the methodology and its rules, only closing prices were considered. It was assumed that:

1. An investor had R500 starting capital.
2. The investor needed to invest in all signals triggered, as per the above rules, specifically by the current top 40 companies of the JSE.
3. The *ex*-dividend days were clearly communicated to the market.

If there were overlaps (i.e., multiple entry signals), the investor needed to make provisions for this so that she could meet assumption 2. This meant that at times, the capital would have been split up into equal portions, the number depending on the *ex*-dividend days in a given period. An example of this splitting between positions can be seen in Table 1, which reflects the year 2004.

From the period 1 January 2004 until 6 October 2014, 248 trades were effected based on the entry and exit rules. The results are presented in Figure 3.

Figure 3. Testing for dividend footprints reveals a positive skew



In the above figure, the distribution of the losing and winning trades are represented. To the left of 0% we have two columns (red), the first measuring losses between 0 and 4.99%, which includes 80 trades. The second measures losses between 5% and 9.99% and totaled 20 trades. The green columns to the right of 0% show the profitable positions. The first green column (0–4.99%) is indicative of 86 trades; the second (5%–9.99%) includes 39 trades. Of note, the positive side continues to plot well beyond 9.99%.

The 10%–14.99% column represents 14 trades, and the 15%–19.99% column includes five trades. And then there are a few "outliers" as far as the 25%–29.99% column (two trades in each of the last two green columns).

This is significant and implies, in essence, that there is a positive skew distribution. Indeed, there is notable buyer activity as time tends towards the *ex*-dividend date. Remember, it was the *ex*-dividend day that was the sole determinant in marking the countback day—the proverbial footprints in the sand.

Discussion

Establishing the Existence of a Dividend Force

It is argued herein that dividends do exert a force on the momentum of price and, in doing so, leave a signature footprint. This is due to their inherent nature of providing signals to the market and their relative stability in being paid.

Dividend Signaling

Signaling theory theorizes that the managers of a company have access to information that investors do not. Therefore when a firm announces a change to its dividend policy, they are in fact conveying such information to the market. This suggests that a profitable company with good prospects ahead of it will behave differently to unprofitable companies that have gloomy times ahead.

Dividend payments is one such distinct behavior. In other words the less prosperous company will be reluctant to pay a dividend. It follows then that dividends are likely to be interpreted as positive by investors, especially if they are increasing.

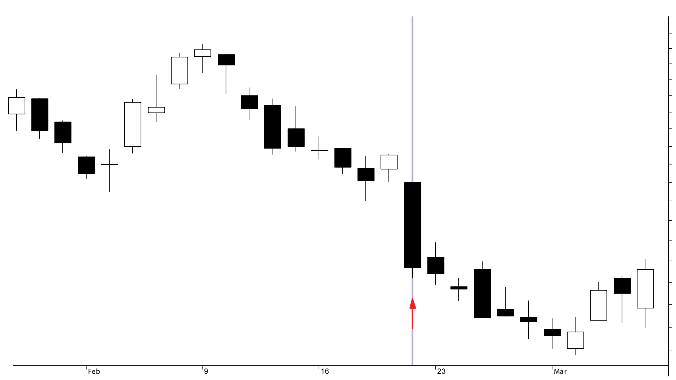
In their conclusion, Connelly and others (2011) write, "signaling theory provides a unique, practical and empirically testable perspective on problems of social selection under conditions of imperfect information…The fact that researchers…use signaling theory to explain selection phenomena in their own disciplines is reassuring."

Dividend Signaling in Action

If a company with a history of a good, steady, predictable dividend payout suddenly cuts its dividend,this is treated as a signal of trouble ahead for the company. Usually these companies are punished by the market.

For example, on 20 February 2009, South African-listed stalwart Anglo American (AGL) announced a suspension of its dividend payment. Then, CEO Cynthia Carroll stated, "we've made the extremely difficult decision to suspend our dividend." The result was a punishing 15.9% fall in the AGL stock price intraday.[3] Consider Figure 4 in this regard.

Figure 4. The 15.9% intraday drop in AGL following the suspension of its dividend



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Dividend Policy in South Africa

This being the case, it is important to note that dividends in of themselves are relatively predictable in their timing. For example, FirstRand Limited (FSR) and BHP Billiton (BIL) have had a relatively consistent *ex*-dividend history in recent times, as per Table 2.

These are not isolated cases. By and large, the dividend declarations (and more importantly for our purposes, the *ex*-dividend day) are fairly consistent in terms of date, and if there is a change, the stability of the declarations reestablishes over time.

According to Firer and others (2008) "[the] survey of 145 JSE listed companies by Seneque and Gourley (1983) established that management...pursued dividend policy as an active variable, and strongly supported the view that continuity of payments and stable payout ratios were of great importance. When setting dividend policy, respondents were chiefly influenced by 'recorded earnings and the prospects of future earnings.'"

This was corroborated by Marx (2001), who found that financial directors of JSE listed companies felt that dividend policy changes should be communicated to investors (Firer and others 2008). This is a remarkable point because it does have a strong suggestion that *ex*-dividend dates have a stable and consistent element to them, and any deviations thereof will be made known to the market. This is not to say that surprises don't occur, rather the author acknowledges that they do. However, it does imply that empirical testing can and should be applied with a sense of confidence.

Table 2. *Ex*-dividend dates tend to be stable

FSR Ex -Dmdend Date	BILEx -Dmdend Date
2004-03-19	
2004-10-18	
2005-03-17	2005-02-28
2005-10-17	2005-09-05
2006-03-17	2006-02-24
2006-10-16	2006-09-04
2007-03-16	2007-02-26
2007-10-15	2007-09-10
2008-03-20	2008-02-25
2008-10-20	2008-09-01
2009-03-30	2009-02-23
2009-10-12	2009-08-31
2010-03-26	2010-03-01
2010-10-11	2010-09-06
2011 -03-28	2011 -03-07
2011 -10-10	2011 -09-05
2012-03-16	2012-02-27
2012-10-08	2012-09-03
2013-03-22	2013-03-04
2013-10-07	2013-09-02

The Tools

Given that the testing point of this paper was the footprints, if any, dividends leave that influence price momentum, the technical tools needed to be specific. In other words, price signals themselves became unimportant to the testing, as the *ex*-dividend day was the catalyst for entry. This being the case, the technical tools and indicators chosen needed to be adequate in assessing the trail of footprints left by the market participants chasing the dividend payments. To this end, volume became the logical choice of indicator.

Volume Analysis

Volume is the number of stocks traded in a period. This variable is of particular importance because it is not derived from price, which as already alluded to, plays no part in the entry here. Volume generally provides independent evidence to confirm stock price analysis and in this instance is used to confirm buying vigor prior to the *ex*-dividend day. However, volume histograms are generally difficult to interpret in terms of analyzing whether market participants are accumulating or distributing stock.

On-Balance Volume (OBV)

OBV is a good indication of buying and selling pressure in the market. It is a cumulative indicator that adds volume on an up day and subtracts volume on a down day. The key here is the word "day." OBV is a daily indicator and is less effective on weekly or monthly charts.

Consider the following scenario: A trading week for company XYZ Limited closes marginally up on four of its five days and down on the fifth day, making it a down week for that specific company. Now assume that the four up days had considerable volume, and the down day had a much lower volume. In other words, there was a fair amount of accumulation during the week. On the daily chart, OBV would be positive, but on the weekly chart, it will be distorted and reflect as a negative. This is an important distinction and implies that the methodology conducted only included volume data gleaned from the daily chart.

OBV was developed by Joe Granville and introduced in 1963 when he published his book *Granville's New Key to Stock Market Profits*. Granville saw volume as an excellent way to determine the balance between supply and demand. He hypothesized that volume precedes price. In other words, a positive volume is indicative of higher prices ahead. Granville's research indicated that OBV would often lead to higher prices. The absolute value is not important but rather the fact the OBV exhibits a positive direction.

Common Dividend Strategies

The most basic strategy to take advantage of company dividends is the simple buy and hold. Investors typically buy good quality stocks that pay dividends and simply collect these as they are declared, ceteris paribus. The danger here is that during deep recessions, such as the global financial crisis and the market plunge of 2008, capital losses are extremely damaging to a portfolio, and the companies themselves may find themselves in a difficult position, whereby they cut their dividends, as per the AGL case above.

A more advanced strategy is called dividend stripping. This is an attempt to buy a stock and profit from a potential price run before the *ex*-dividend date and then potentially pick up further gains as the stock recovers after going *ex*-dividend. However, consider Figure 5 of Shoprite Limited (SHP):

Figure 5. After recovering slightly post *ex*-dividend, SHP then continues lower

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There is indeed a run up to the *ex*-dividend date of 8 September 2014 (green arrow), and then the price seems to drift before exhibiting a lower peak and then resuming its downtrend (red arrow).

A Peculiar Occurrence

In Australia, investors are allowed to collect franking credits from a dividend. This is a type of dividend imputation and is used to reduce or eliminate the double taxation of dividends. However, the Australian Tax office enacted legislation whereby if an investor earns more than AUD 5,000 per annum in dividends, the stock must be held for 45-days or more. This was enacted to eliminate the capture of franking credits by short-term investors.

However, according to Ainsworth and others (2008), "despite the introduction of the 45-day rule, changes in the taxation of capital gains and the refunding of unutilized franking credits, abnormal price behavior continues to occur around the *ex*-dividend day."

In other words, there is an element of consistency in the behavior of investors around the *ex*-dividend date despite attempts by legislative bodies to discourage such behavior. There are indeed footprints that are being left behind by market participants around the *ex*-dividend date.

Dividend Buyer's Momentum

To uncover these footprints, it is understood that there is a certain enthusiasm or vigor that is exhibited by dividend seekers. As such, appropriate indicators were selected to track this. First, the introduction of the 200-day simple moving average made sense. The testing required the countback day's low to be above the 200-day SMA, as this discounted the negative momentum and disqualified offending stocks from possible selection. Thus, candidates left over had neutral to positive momentum in their price movements.

Secondly, the MACDOBV Histogram proved to be a good indicator of the buyer enthusiasm. There is good reason that the author opted to use this derived indicator. The MACD Histogram measures the distance between the MACD and its 9-period EMA. It is similar to the MACD in that it oscillates above and below zero. However, its creator, Thomas Aspray,[4] intended it to anticipate signal line crossovers in MACD.

MACD is derived from moving averages that inherently lag price, and the divergences in the MACD Histogram can alert financial technicians to approaching MACD crossovers. Negative value in the MACD Histogram decrease as MACD converges on its signal line. Likewise, positive values increase as MACD diverges further from its signal line. Thus, momentum is captured and represented succinctly.

Given the seemingly stable nature of dividends, it would seem to make sense that investors would act to take advantage of these payments. If this is so, then investor accumulation should carry these signature footprints, and this purchasing of stock would be particular to the period prior to the *ex*-dividend payment date. Price signals are essentially meaningless to this study because the entry is taken from the *ex*-dividend date. However, volume is not.

On the contrary, volume now becomes incredibly important in tracking the footprints because, according to Granville, volume leads price. Thus, application of the MACD Histogram to OBV instead of price and taking cognizance of the bearish diverge, positive to negative crossovers, or failure to gain any traction to move into positive territory will let the savvy market technician know that buyer enthusiasm is waning. This being the case, the exploitation thereof becomes possible.

The Exploitation of Dividends for Profit

The Sharpe Ratio

As seen above, the proverbial footprints exist. The question that follows then is whether it is worth taking note of this activity? Can this activity truly be exploited?

To answer adequately, one must consider the risk-adjusted returns earned by following the footprints. To be clear, the earnings themselves are secondary, we have already determined that the footprints exist by the positive skew in Figure 3. We now wish to examine their exploitation for gain and assess the worthiness of such action.

The Sharpe ratio (Sa) measures the efficiency of a portfolio. A higher ratio equates to a more efficient portfolio performance and is calculated by the following equation:

$$S_a = E[R_a - R_b]/\sigma_a$$
$$= E[R_a - R_b]/\sqrt{var[R_a - R_b]}$$

Table 3. Returns and risk-adjusted returns of tracking dividend footprints

Year	Return	Risk Free Rate[5]	Risk Adjusted
2004	19,35	7,75	11,60
2005	2,54	7,25	-4,71
2006	15,18	8	7,18
2007	-4,60	10	-14,60
2008	18,28	11,25	7,03
2009	35,40	9,25	26,15
2010	17,10	6,25	10,85
2011	15,78	5,5	10,28
2012	2,36	5,25	-2,89
2013	24,40	5	19,40
2014	-0,33	5,38	-5,71

$S_a \quad = E[R_a\text{-}R_b]/\sigma_a$

$\quad\quad = E[R_a\text{-}R_b]/\surd var[R_a\text{-}R_b]$

Where R_a is the asset return, R_b is the risk free rate, and σ is the standard deviation of this excess return. In this case $[R_a\text{-}R_b]$ is 5.87 and σ is 11.9

Therefore: 5.87/11.9 = 0.49

Consider the 0.49 against a buy and hold strategy of the Top 40 index for the same time period. The buy and hold is affected through the exchange trade fund SATRIX 40 (STX40):

Table 4. Returns and risk-adjusted returns of buy and hold

Year	Return	Risk Free Rate[5]	Risk Adjusted
2004	10,00	7,75	2,25
2005	33,33	7,25	26,08
2006	35,29	8	27,29
2007	13,04	10	3,04
2008	-29,63	11,25	-40,88
2009	25,00	9,25	15,75
2010	16,00	6,25	9,75
2011	0,00	5,5	-5,50
2012	20,69	5,25	15,44
2013	13,89	5	8,89
2014	4,76	5,375	-0,61

In the case of STX40, $[R_a\text{-}R_b]$ is 5.59 and σ is 18.6

Therefore: 5.59/18.6 = 0.30

This would indicate that following the footprints of dividends and exploiting these for personal gain and profit is a more efficient strategy than a simple buy and hold strategy of the Top 40 index.

Conclusion

This paper examined the question of whether dividends or more specifically, dividend seekers, leave a trail of their activity in the market. Indeed, it was found that their purchasing enthusiasm and vigor do leave a trail of footprints, as shown by the positive skew of Figure 3. To arrive at this conclusion, a rules-based approach that included very specific indicators was followed, which allowed for empirical testing. Moreover, once these footprints were confirmed, the paper examined whether these could be exploited for profit. Using the Sharpe ratio and making an accounting for risk-adjusted returns, the conclusion was that the footprints can be tracked and exploited for gain.

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Notes

[1] The MACD is the difference between the 26-period EMA and the 12-period EMA, and its signal line is a 9-period EMA of the MACD.

[2] This includes the countback day. It is not the countback day plus another five days.

[3] Incidentally, the rule-based approach, although constructed for testing only, as discussed herein would have protected market participants from this painstaking loss.

[4] Aspray developed the MACD Histogram in 1986.

[5] The South African Reserve Bank Repurchase Rate was used as a proxy for the risk free rate. It was calculated by taking the rate at the end of the year plus the rate at the beginning of the year and then dividing by 2.

Lumber: Worth Its Weight in Gold—Offense and Defense in Active Portfolio Management

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Abstract

Prior academic research focuses on commodities in isolation as leading economic indicators, ignoring the message price behavior may have on other asset classes. We find that the relative movement of Lumber to Gold provides important information on economic growth and inflation expectations, which gradually diffuses with a lag to stock and bond markets. Lumber's sensitivity to housing, a key source of domestic economic growth in the U.S., makes it a unique commodity, as it pertains to macro fundamentals and risk-seeking behavior. On the opposite end of the spectrum is Gold, which is distinctive in that it historically exhibits safe-haven properties during periods of heightened volatility and stock market stress. We find that the relationship between Lumber and Gold helps to answer the critical question of when to "play defense" and when to "play offense" within the context of active portfolio management. In this paper, we show that a strategy using the signaling power of Lumber and Gold results in stronger absolute and risk-adjusted returns than a passive buy-and-hold index. This outperformance stems from being more aggressive in a portfolio during periods when Lumber is leading Gold and being more defensive during periods when Gold is leading Lumber. The results are robust to various timeframes and across multiple economic and financial market cycles.

Introduction

Active portfolio management rests on the belief that it is possible to outperform the "market," either on an absolute or risk-adjusted basis, by executing a strategy that in some way deviates from a passive buy-and-hold portfolio. The Efficient Market Hypothesis (EMH) states that such outperformance through active management is largely impossible because prices incorporate and reflect all relevant information.[1] However, there are a number of market studies that have disproven the null hypothesis of this theory. Two of the strongest and most well-known anomalies are the "value" effect and the "momentum" effect.[2]

Such studies tend to be asset-class specific, documenting potential outperformance by looking for unique factors specific to the asset class being analyzed. In this paper, we take a different approach and look across asset classes to determine if there is information contained in one area of the investable landscape (commodities) that can be applied to another (equities). Specifically, we show how Lumber and Gold contain important information on macro fundamentals and how their relative movement/momentum impacts risk-seeking and risk-averse behavior in stocks.

We propose that the factors that impact Lumber and Gold spill over to equity investors and traders who, with a lag, respond to that information in a consistent and repeatable way over time. As Lumber outperforms Gold, equities tend to exhibit an upward bias and have lower volatility. These are conditions that are conducive to maintaining higher exposure to risk assets. As Gold outperforms Lumber, the opposite tends to be true, whereby the inclusion of lower beta assets in a portfolio increases overall return and lowers volatility at the time it is needed most.

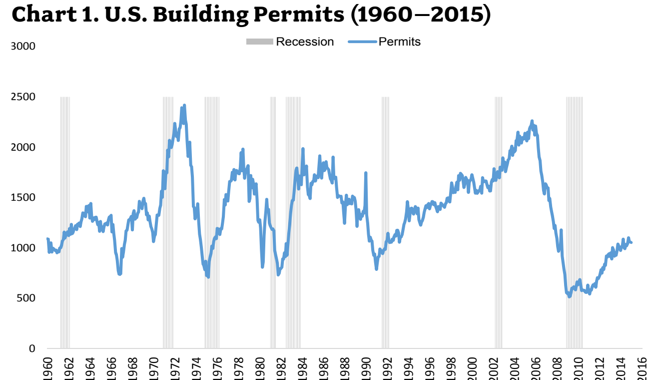
The relationship between Lumber and Gold helps to answer the most critical question for active asset managers: when to take more risk ("play offense") and when to take less risk ("play defense") in an investment portfolio—before it's too late.

Lumber as a Cyclical Leading Indicator

Lumber futures receive little attention as compared to industrial metals such as Copper, which are often viewed as leading indicators of economic growth. Investors may be underestimating Lumber's importance, though, as housing and construction tend to be major components of the business cycle.[3] Housing greatly "influences the level of consumer spending" and is the "primary store of wealth for most Americans."[4]

It should come as no surprise, then, that housing permits are one of the key leading economic indicators in the U.S., ranking ahead of the S&P 500 in their ability to signal a turn in the economy.[5] Leamer (2007) showed that housing is "the most important sector in our economic recessions" and residential investment is often "the first item to soften and the first to turn back up" before and after recessions. We can readily observe these leading characteristics in Chart 1.

Chart 1. U.S. Building Permits (1960–2015)



Given that "an average new home built in the U.S. contains over 14,000 board feet of lumber," the demand for Lumber is uniquely sensitive to housing activity.[6] By extension, this makes Lumber futures highly responsive to anticipated construction activity. Rucker, Thurman, and Yoder (2005) confirm this, showing that lumber futures react quickly to housing starts data released on a monthly basis. Clements, Ziobrowski, and Holder (2011) also find that timberland market values are strongly influenced by six-month lumber futures and building permits. The efficiency with which Lumber reacts to such data suggests that its price movement can be important as a leading indicator of cyclical growth and rising inflation expectations.

In addition to Lumber's sensitivity to planned construction and actual building, the commodity is unique in terms of regulation's impact on its available supply. The Endangered Species Act of 1973 was passed to protect species at risk of extinction due to economic activity.[7] Logging and deforestation has been reduced over time due to court rulings which protected not only endangered species but also their ecosystems.[8] It is estimated that "one-third of the forestland in the United States is publicly owned and has been withdrawn from production… [and] of the remaining 500,000 acres, 29% is publicly owned and contributes very little to the Nation's timber output."[9]

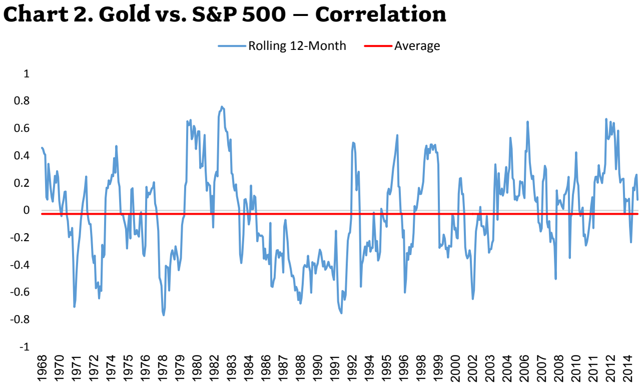
Regulation that prevents significant new supply suggests that Lumber will be highly sensitive to housing activity and economic demand fluctuations. This in turn makes it a cyclical leading indicator of not only the economy, but also the stock market, which experiences expansionary phases that are tied to cyclical growth and consumer demand. That consumer demand is driven in large part by housing and construction activity, which is reflected in the price of Lumber in real time.

Gold as a Non-Cyclical and Uncorrelated Commodity

Gold is a particularly interesting commodity in the context of its historical role as a store of value and given the unique properties the precious metal has in terms of being an alternative asset. Lawrence (2003) showed that there is "no statistically significant correlation between returns on gold and changes in macroeconomic variables such as GDP, inflation, and interest rates…[and that] returns on Gold are less correlated with returns on equities and bond indices than are returns on other commodities." This makes Gold unique relative to cash, which has more consistent counter-cyclical properties in bear markets or contractionary economic environments.

Since January 1976, Gold's monthly correlation with the Barclays US Aggregate Bond Index is .05, while its correlation with the S&P 500 is .02. Chart 2 illustrates the lack of any consistency in Gold's correlation with U.S. equities.

Chart 2. Gold vs. S&P 500 — Correlation



In addition to the historical non-correlation that Gold has to stocks and bonds, the precious metal also tends to exhibit safe-haven characteristics. Baur and Lucey (2010) show that Gold "is a hedge against stocks on average and a safe haven in extreme stock market conditions … Furthermore, gold is not a safe-haven for stocks at all times but only after extreme negative stock market shocks." Additional studies show that "Gold … has a positive relationship with [stock market] implied volatility, supporting the idea that investors perceive precious metals as safe havens, to be purchased in anticipation of rising equity market volatility."[10]

The risk-aversion characteristics of Gold make for a natural baseline to which we can assess changes in the price of cyclical Lumber. While seemingly at the opposite ends of the economic spectrum, the yin and yang of Lumber and Gold are actually highly complementary, as we will soon see.

The Lumber-Gold Trading Rule

Combining cyclical Lumber with non-cyclical Gold provides key information on when to "play offense" and when to "play defense" in an investment portfolio.

Using weekly data available on Lumber and Gold going back to November 1986, we developed the following trading rule:[11]

*If **Lumber** is **outperforming** Gold over the prior 13 weeks, take a **more aggressive** stance in the portfolio for the following week.*

*If **Gold** is **outperforming** Lumber over the prior 13 weeks, take a **more defensive** stance in the portfolio for the following week.*

***Re-evaluate weekly** and make changes to the portfolio only when leadership between Lumber and Gold changes.*

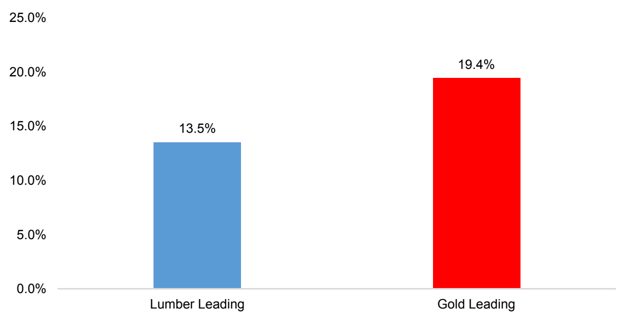
Research has shown that commodities exhibit momentum in various timeframes from 1 month through 12 months, with the strongest momentum exhibited in the 3-month period.[12] Three months equates to 13 weeks, which is the timeframe used in this paper.[13]

The Market Environment and the Volatility Signal

Before we examine active strategies based on the Lumber-Gold trading rule, it is important to understand why a more aggressive position is warranted when Lumber is outperforming and why a more defensive position is warranted when Gold is outperforming. The critical factor is volatility, whereby Lumber's leadership is forecasting lower volatility in the stock market, while Gold leadership is signaling higher volatility.

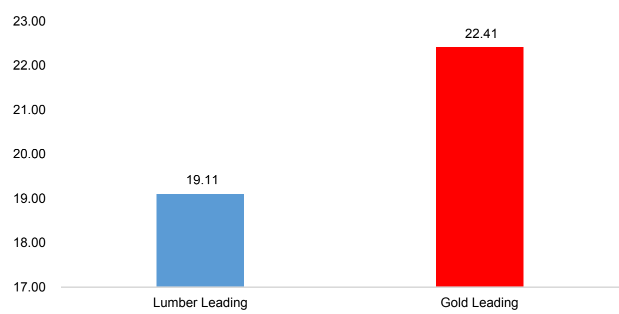
We can observe this in examining the actual S&P 500 volatility in the week following Lumber and Gold outperformance. When Lumber is leading, the average annualized S&P 500 volatility (standard deviation) is 13.5% in the following week, versus 19.4% when Gold is leading (see Chart 3).

Chart 3. S&P 500 Average Annual Volatility



We also observe a meaningful difference in implied volatility (VXO Index) depending on whether Lumber or Gold is leading.[14] When Gold is outperforming, the average VXO Index value was 22.4 in the following week, versus 19.1 when Lumber is leading (see Chart 4).

Chart 4. VXO Index (Average Values)



Finally, we looked at the largest weekly percentage declines for the S&P 500 during the sample period. We found that in the worst 5% of weeks, Gold was outperforming in advance 74% of the time, and in the worst 1% of weeks, Gold was outperforming in advance 87% of the time. This is significantly higher than the percentage of time Gold was outperforming overall at 49%.

The impact that substantial differences in volatility can have on a portfolio cannot be overstated. Low-volatility environments tend to be more favorable for risk assets and more conducive to offensive positioning. On the other hand, higher volatility environments are the enemy of beta and risk, making defensive positioning more desirable.

Defense vs. Offense: Developing Objective Criteria

The concept of "playing defense" and "playing offense" in active portfolio management can be subjective and is highly dependent on one's overall risk tolerance. To make the decision-making process more objective, we illustrate a spectrum of indices (moving from more defensive to more offensive) in Table 1 based on their volatility and beta to the S&P 500.

Table 1. Asset Class Volatility and Beta

Asset Class	Annualized Volatility	Beta to S&P 500
BofA Merrill Lynch 5-7 Year Treasury Index	4.83%	-0.04
CBOE S&P 500 Buy-Write Index	11.6%	0.63
S&P 500 Low Volatility Index	12.5%	0.63
S&P 500 Index	16.7%	1.00
Russell 2000 Index	20.1%	1.02
Morgan Stanley Cyclicals Index	22.9%	1.17
S&P 500 High Beta Index	31.2%	1.66

Within this paper, we will focus on strategies using some combination of the above asset classes. We recognize this is a limited list and there are many more ways to play defense and offense within a portfolio.

Playing Defense When Gold Is Outperforming Lumber

When Gold is outperforming Lumber, you want to play defense on average. There are a number of ways that investors can express a more defensive stance in an investment portfolio. If we assume that the starting point is a 100% equity portfolio invested in the S&P 500, a more defensive portfolio can be achieved by: 1) rotating into Treasury bonds, 2) introducing hedges or employing a buy-write strategy, or 3) rotating into lower beta/volatility equities.

1) The Lumber-Gold ("LG") Bond Strategy

In our research, we found that the single best way to consistently play defense over time is to rotate into a low or negatively correlated asset class in which you are not highly penalized when you are wrong. U.S. Treasury bonds satisfy both of these criteria. The reason why we do not use shorting or cash as a defensive play is due to false positives that are inherent in any risk management strategy. In this case, a false positive arises when Gold is leading Lumber without a concurrent increase in volatility or a decline in stocks. Sitting in cash or using short positions during such times would be highly damaging to returns while being in bonds of some duration can still provide a positive expected return on average.

Since November 1986, the weekly correlation between the S&P 500 Index and the BofA Merrill Lynch 5-7 Year Treasury Index is -.12.[15] During weeks in which the S&P 500 returns are negative, this correlation moves down to -.21. This negative correlation is important because it provides the opportunity to generate positive absolute returns when stocks are declining, something few asset classes can do on a consistent basis.

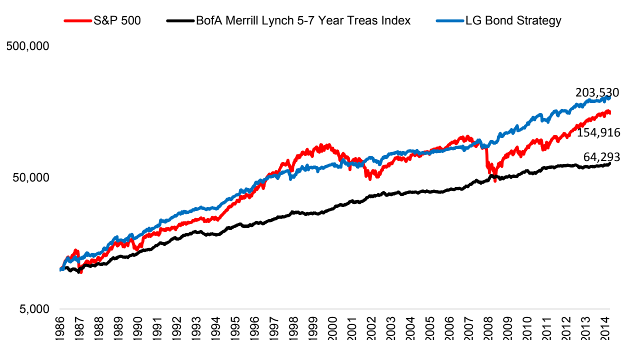
Rotating into the 5-7 Year Treasury Index when Gold is outperforming Lumber and maintaining stock exposure when Lumber is outperforming Gold (the "LG Bond Strategy") improves both absolute and risk-adjusted return metrics. Annualized returns are higher (11.2% vs. 10.1%), but more importantly, the Sharpe and Sortino ratios are significantly higher with lower volatility (10.2% vs. 16.7%) and drawdowns (-14.5% vs. -54.7%) than a buy-and-hold S&P 500 portfolio. This is illustrated in Table 2 (note: all performance data in this paper is total return).

Table 2. LG Bond Strategy vs. S&P 500 (Nov 1986–Jan 2015)

	LG Bond Strategy	S&P 500	Differential
Cumulative Return	1935%	1449%	486%
Annual Return	11.2%	10.1%	1.1%
Annual Volatility	10.2%	16.7%	-6.5%
Sharpe Ratio	0.57	0.29	99%
Sortino Ratio	0.85	0.40	111%
Max Drawdown	-14.5%	-54.7%	40.2%
Beta	0.3	1	-0.70
Annual Alpha	4.4%	0.0%	4.4%
Rotations/Year	6.8	0	6.8

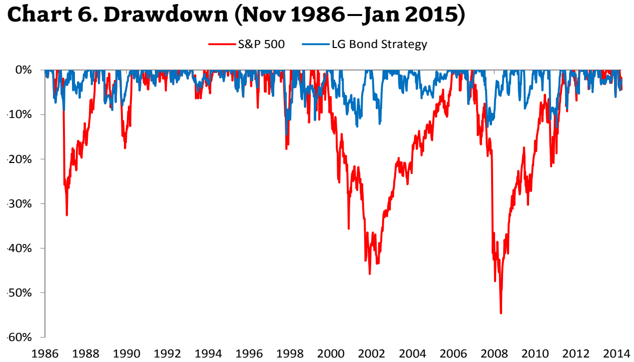
The consistency of the lower volatility profile can be observed more readily in Chart 5, which shows the growth of $10,000 over time. The smoothness of the LG Bond Strategy's return path relative to the S&P 500 is critical for investment managers and their clients, as the ability to stick to a strategy often matters more than the strategy itself. High drawdowns and volatility increase the likelihood of selling an investment at the worst possible time.

Chart 5. Growth of $10,000 (Nov 1986–Jan 2015)



We can also see this in viewing a chart of drawdowns over time, where the LG Bond Strategy has consistently lower drawdowns during periods of equity market stress (see Chart 6).

Chart 6. Drawdown (Nov 1986–Jan 2015)



Another way to confirm this is in looking at the largest drawdowns (on a weekly basis) for the S&P 500 since 1986. Market historians will recognize each of these instances that include three recessionary (1990, 2000-02, and 2007-09) and three non-recessionary (1987, 1998, and 2011) periods of market stress. In each of these occasions, the LG Bond Strategy protected capital with a significantly lower drawdown than a buy-and-hold position in the equity market.

Table 3. Largest S&P 500 Drawdowns (Nov 1986–Jan 2015)

Start Date	End Date	LG Treas Bond Max Drawdown	S&P 500 Index Max Drawdown	Differential
8/21/1987	12/4/1987	-9.0%	-32.6%	23.6%
7/13/1990	10/12/1990	-8.0%	-17.6%	9.6%
7/24/1998	10/9/1998	-14.5%	-17.8%	3.3%
3/24/2000	10/4/2002	-12.7%	-45.8%	33.1%
10/12/2007	3/6/2009	-12.8%	-54.7%	41.9%
4/29/2011	10/7/2011	-11.1%	-17.0%	6.0%

2) The Lumber-Gold ("LG") BuyWrite Strategy

For investors that would prefer to maintain a position in the S&P 500 rather than rotating into bonds, another way to achieve a more defensive position is to use options to hedge a portfolio when Gold is outperforming Lumber. To replicate such a strategy, we used the CBOE S&P 500 BuyWrite Index, which is a total return index based on (1) buying a S&P 500 stock portfolio and (2) "writing" or (selling) the near-term S&P 500 "covered" call option, generally on the third Friday of each month.[16]

As illustrated in Table 4, executing the LG BuyWrite Strategy improves risk-adjusted returns and lowers volatility and drawdown, but not nearly to the same extent as shifting into bonds. This should be intuitive, as the weekly correlation between the BuyWrite Index and the S&P 500 is still very high at .93. When stocks go down, then your expectation in using the BuyWrite Index as a hedge is to simply lose less money, as it does not give you the opportunity to generate a positive absolute return.

Table 4. LG BuyWrite Strategy vs. S&P 500 (Nov 1986–Jan 2015)

	LG BuyWrite Strategy	S&P 500	Differential
Cumulative Return	1479%	1449%	30%
Annual Return	10.2%	10.1%	0.1%
Annual Volatility	13.8%	16.7%	-2.9%
Sharpe Ratio	0.35	0.29	23%
Sortino Ratio	0.48	0.40	19%
Max Drawdown	-43.1%	-54.7%	11.6%
Beta	0.78	1	-0.22
Annual Alpha	1.1%	0.0%	1.1%
Rotations/Year	6.8	0	6.8

3) The Lumber-Gold ("LG") Low Volatility Strategy

For investors that would prefer to lower their beta to the market as their expression of risk management, a more defensive position could be achieved by rotating into lower volatility stocks. The S&P 500 Low Volatility Index dates back to November 1990 and measures the performance of the 100 least volatile stocks in the S&P 500.

Rotating into the Low Volatility Index ("LG Low Vol Strategy") when Gold is outperforming Lumber improves absolute and risk-adjusted returns, lowers overall beta, and generates 2.5% alpha per year (see Table 5).

Table 5. LG Low Vol Strategy vs. S&P 500 (Nov 1990–Jan 2015)

	LG Low Vol Strategy	S&P 500	Differential
Cumulative Return	1293%	937%	356%
Annual Return	11.5%	10.1%	1.3%
Annual Volatility	14.1%	16.6%	-2.5%
Sharpe Ratio	0.44	0.29	51%
Sortino Ratio	0.61	0.41	51%
Max Drawdown	-44.4%	-54.7%	10.3%
Beta	0.76	1	-0.24
Annual Alpha	2.5%	0.0%	2.5%
Rotations/Year	6.9	0	6.9

It is interesting to note that the LG Low Volatility strategy has a similar risk profile to the LG BuyWrite Strategy but with improved risk-adjusted return metrics and higher alpha. This suggests that rotating into lower volatility equities may provide a more effective hedge than employing a buy-write strategy.

Playing Offense When Lumber Is Outperforming Gold

When Lumber is outperforming Gold, you want to play offense on average. There are a number of ways that investors can express a more aggressive stance in an investment portfolio. If we again assume that the starting point is a 100% equity portfolio invested in the S&P 500, a more offensive portfolio can be achieved by: 1) rotating into small cap equities, 2) rotating into higher beta stocks, or 3) rotating into cyclical sectors.

1) The Lumber-Gold ("LG") Small Cap Strategy

Small caps are traditionally higher beta and higher volatility equities and tend to perform better during expansionary periods. Their revenues are also more domestically focused than multi-national large caps and by extension tend to be more sensitive to cyclical swings in housing and the U.S. economy. When Lumber is outperforming, then we would expect on average to see small cap leadership.

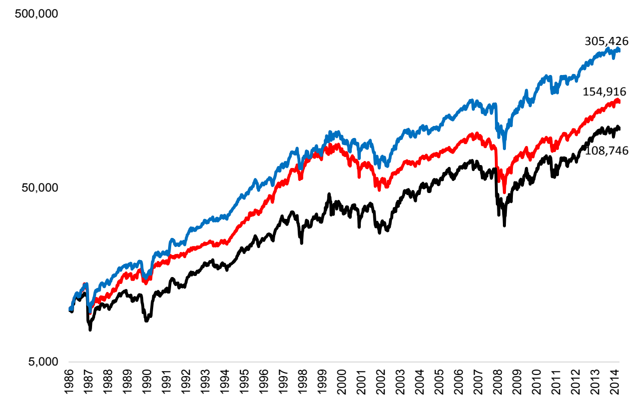
By rotating into the Russell 2000 Index when Lumber is outperforming Gold, an investor would have picked up an additional 2.7% per year of annualized returns over the S&P 500 with improved risk-adjusted metrics as well. Volatility is higher for this strategy than the S&P 500 (17.7% vs. 16.7%), but given the alpha of 2.8% per year, you are being compensated for this higher volatility (see Table 6).

Table 6. LG Small Cap Strategy vs. S&P 500 and Russell 2000 (Nov 1986–Jan 2015)

	Russell 2000	S&P 500	LG Small Cap Strategy	LG - S&P
Cumulative Return	987%	1449%	2954%	1505%
Annual Return	8.8%	10.1%	12.8%	2.7%
Annual Volatility	20.1%	16.7%	17.7%	1.0%
Sharpe Ratio	0.17	0.29	0.42	47%
Sortino Ratio	0.23	0.40	0.59	47%
Max Drawdown	-58.0%	-54.7%	-47.5%	7.2%
Beta	1.02	1	0.97	-0.03
Annual Alpha	-1.5%	0.0%	2.8%	2.8%
Rotations/Year	0	0	6.8	6.8

Chart 7 shows the growth of $10,000 for the strategy, which is significantly higher than both the Russell 2000 and the S&P 500.

Chart 7. Growth of $10,000 (Nov 1986–Jan 2015)



2) The Lumber-Gold ("LG") High Beta Strategy

For investors with a high risk profile, rotating into high beta stocks when Lumber is outperforming Gold is a second option. The S&P 500 High Beta Index measures the performance of the 100 constituents in the S&P 500 that are the most sensitive to changes in market returns.

Going back to November 1990, rotating into the High Beta Index during periods when Lumber is outperforming results in an annualized return that is 1.9% higher than the S&P 500. There is no free lunch with high beta stocks, though, as volatility in this strategy is significantly higher as is the maximum drawdown. However, with annualized alpha of 0.9% per year, you are again being compensated for this additional risk (see Table 7).

Table 7. LG High Beta Strategy vs. S&P 500 (Nov 1990–Jan 2015)

	LG High Beta Strategy	S&P 500	Differential
Cumulative Return	1487%	937%	550%
Annual Return	12.1%	10.1%	1.9%
Annual Volatility	23.3%	16.6%	6.6%
Sharpe Ratio	0.29	0.29	0%
Sortino Ratio	0.43	0.41	5%
Max Drawdown	-67.5%	-54.7%	-12.8%
Beta	1.22	1	0.22
Annual Alpha	0.9%	0.0%	0.9%
Rotations/Year	6.9	0	6.9

3) The Lumber-Gold ("LG") Cyclical Strategy

For investors preferring to use stocks tied to the business cycle as the offensive position, cyclicals are a natural fit. Using the Morgan Stanley Cyclicals Index (from November 1986 to July 2013) and the US Cyclical Equity Index (from July 2013 to January 2015), we find that the absolute and risk-adjusted returns improve relative to a constant buy-and-hold of the S&P 500. Similar to the High Beta Index, though, using the cyclical indices as the aggressive position increases overall volatility and maximum drawdown. With annualized alpha of 2.9% per year, you are being compensated for this additional risk.

Table 8. LG Cyclical Strategy vs. S&P 500 (Nov 1986—Jan 2015)

	Cyclical Index	S&P 500	LG Cyclical Strategy	LG - S&P
Cumulative Return	1664%	1449%	3298%	1849%
Annual Return	10.7%	10.1%	13.2%	3.1%
Annual Volatility	22.9%	16.7%	19.1%	2.4%
Sharpe Ratio	0.23	0.29	0.41	44%
Sortino Ratio	0.33	0.40	0.59	48%
Max Drawdown	-73.3%	-54.7%	-55.6%	-0.9%
Beta	1.17	1	1.04	0.04
Annual Alpha	-0.3%	0.0%	2.9%	2.9%
Rotations/Year	0	0	6.8	6.8

Putting It All Together: Combining Defense and Offense

Now that we have explored playing offense and defense individually, the next step for an active investment manager is to employ a strategy that combines the two.

There are various combinations that can be utilized depending on the desired risk profile of the portfolio and use of instruments. For investors targeting a lower drawdown, lower volatility, and lower beta while maintaining simplicity in a portfolio, the strongest combination is to use either Small Cap or Cyclical stocks when Lumber is outperforming Gold and Treasury bonds when Gold is outperforming Lumber.

1) The Lumber-Gold ("LG") Small Bond Strategy

In Table 9, we see that a strategy that rotates between Small Caps on offense and 5-7 year Treasuries on defense produces a return that is 3.8% higher than the S&P 500 with 4.9% lower volatility. The maximum drawdown of -20.8%, while higher than the LG Bond Strategy, is still less than half of the S&P 500 (-54.7%).

Table 9. LG Small Bond vs. S&P 500 (Nov 1986—Jan 2015)

	LG Small Bond	S&P 500	Differential
Cumulative Return	3913%	937%	2976%
Annual Return	13.9%	10.1%	3.8%
Annual Volatility	11.8%	16.6%	-4.8%
Sharpe Ratio	0.73	0.29	153%
Sortino Ratio	1.07	0.41	164%
Max Drawdown	-20.8%	-54.7%	33.9%
Beta	0.28	1	-0.72
Annual Alpha	7.2%	0.0%	7.2%
Rotations/Year	6.8	0	6.8

2) The Lumber-Gold ("LG") Cyclical Bond Strategy

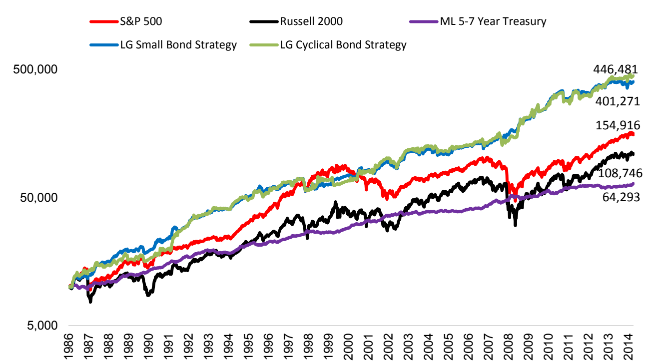
In Table 10, we see that a strategy that combines offense and defense using the Cyclical Index and Treasury bonds produces a return that is 4.2% higher than the S&P 500 with 2.9% lower volatility. The maximum drawdown of -20.2%, while higher than the LG Bond Strategy, is also less than half of the S&P 500 (-54.7%).

Table 10. LG Cyclical Bond vs. S&P 500 (Nov 1986—Jan 2015)

	LG Cyclical Bond	S&P 500	Differential
Cumulative Return	4365%	937%	3428%
Annual Return	14.3%	10.1%	4.2%
Annual Volatility	13.8%	16.6%	-2.8%
Sharpe Ratio	0.65	0.29	127%
Sortino Ratio	1.00	0.41	146%
Max Drawdown	-20.2%	-54.7%	34.4%
Beta	0.35	1	-0.65
Annual Alpha	7.3%	0.0%	7.3%
Rotations/Year	6.8	0	6.8

In Chart 8, we see that the LG Small Bond and LG Cyclical Bond Strategies outperform both stocks and bonds with lower volatility than the equity indices.

Chart 8. Growth of $10,000



Up Capture, Down Capture, and False Positives

What is the key to the 7+% annualized alpha generated by the LG strategies that combine defense and offense? Is it participation on the upside or protecting on the downside? Looking at the up capture and down capture ratios in Table 11, we see that while both are contributors, "playing defense" is the more critical factor.

Table 11. Up Capture vs. Down Capture (Monthly, Nov 1986—Jan 2015)

	LG Cyclical Bond	LG Small Bond
Up Capture	66%	63%
Down Capture	34%	31%
Up/Down Ratio	1.98	2.03

We know this because the strategies generate absolute outperformance of approximately 4% per year but only participate in 63—66% of the upside. Limiting the downside to only 31—34%, however, was more than enough to overcome the lack of full participation on the upside.

This again brings up the important concept of false positives in any trading strategy that incorporates risk management. It is not that every time Gold is leading Lumber you should expect to see a decline in stocks; it's just that the *probability* has increased and that you must move to a defensive asset class *in advance* because you don't know when a large decline is going to ensue.

In order to protect on the downside, then, you have to be willing to give up some upside in return; there is no other way. This is why the up capture of any risk management strategy must fall short of 100%.

For active managers, this is a tradeoff that pays off in the end but can prove frustrating during periods of unrelenting advance, such as the late 1990s technology bubble and the 2013–2014 Quantitative Easing 3 (QE3) period. During such periods, small sample bias often gets the better of many investors. This is precisely why we believe your ability to stick to a strategy often matters more than the strategy itself.

Conclusion

Housing activity is one of most important leading economic indicators in the United States. Lumber is the commodity most sensitive to changes in the housing market, and by extension, it provides a real-time gauge of demand in the sector. On the other end of the spectrum is Gold, which is uncorrelated to the business cycle with safe-haven characteristics.

The unique combination of Lumber and Gold is an intermarket relationship that has been anticipatory of future economic activity and risk appetite across asset classes outside of commodities. We find that when Lumber is leading Gold over the prior 13 weeks, expansionary conditions predominate and volatility tends to fall going forward. Such an environment is favorable to taking more risk in a portfolio or "playing offense." We also find that when Gold is leading Lumber over the prior 13 weeks, contractionary conditions predominate and volatility tends to rise. In this environment, it pays to manage risk in a portfolio, or "play defense."

The gradual diffusion of information generated from the relationship of Lumber and Gold can help active investors manage risk and enhance returns. We find that executing a strategy that positions into defensive-leaning Treasuries when Gold is leading Lumber and aggressive-leaning Small Caps or Cyclical stocks when Lumber is leading Gold results in higher absolute and risk-adjusted returns with lower volatility and lower drawdowns than a buy-and-hold portfolio. The strategy is robust to multiple timeframes, through multiple economic cycles and multiple periods of market stress.

For active managers, there is no more important question than when to play defense and when to play offense. Using the cyclical and non-cyclical relationship of Lumber and Gold provides an actionable answer that has been consistently effective over time.

Further Research

The findings in this paper have important implications on a number of areas of interest for traders and investors, particularly in the use and timing of leverage. The greatest enemy of leverage is volatility. If the relationship between Lumber and Gold is predictive of future volatility, then a strategy can be developed to adjust leverage or gross exposure accordingly. This is an important topic for many traders and asset managers that we will explore in detail in an upcoming research paper.

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Notes

1 See Malkiel (2003).

2 See Asness, Moskowitz, and Pedersen (2013).

3 According to the National Association of Homebuilders, housing contributes 17% to 18% of GDP. See http://www.nahb.org/generic.aspx?genericContentID=66226.

4 See Belsky and Prakken (2004).

5 See Levanon, Ozyildirim, Schaitkin, and Zabinska (2011).

6 *Lumber*. Retrieved in 2015 from http://www.wikinvest.com/commodity/Lumber.

7 See Ruker, Thurman, and Yoder (2005).

8 See Ruker, Thurman, and Yoder (2005).

9 *Lumber*. Retrieved in 2015 from http://www.wikinvest.com/commodity/Lumber.

10 See Jubinski and Lipton (2013).

11 The data source for Lumber and Gold: Bloomberg. Lumber (Ticker: LB1 Comdty) is the random length lumber futures contract, which specifies 110,000 board feet of random length 8-20 softwood 2 x 4s, the type used for rehabbing and construction. Gold (Ticker: XAU Curncy) is the gold spot price quoted as US Dollars per Troy Ounce.

12 See Miffre and Rallis (2007).

13 We found that timeframes as short as 3 weeks and as long as 21 weeks also have predictive power. Due to the higher turnover on shorter timeframes, we decided to focus on the 13-week timeframe for the purposes of this paper. A lower turnover strategy is more applicable to a broader group of investors.

14 The VXO Index is the CBOE S&P 500 Volatility Index. It was the original VIX index with price history dating back to 1986. Source: www.cboe.com/micro/vxo.

15 We chose the 5-7 year Index (Ticker: G3O2 Index), as it best approximates the duration of the average U.S. bond fund and mitigates the impact (relative to longer duration indices) of interest rate swings. As compared to the 5-7 year Index, using the 15+ Treasury Index (Ticker: G8O2 Index) had higher returns with higher volatility, and using the 3-5 year Treasury index (Ticker: G2O2 Index) had lower returns with lower volatility.

16 The SPX call written will have about one month remaining to expiration, with an exercise price just above the prevailing index level (i.e., slightly out of the money). The S&P call is held until expiration and cash settled, at which time a new one-month, near-the-money call is written. Source: Bloomberg, CBOE

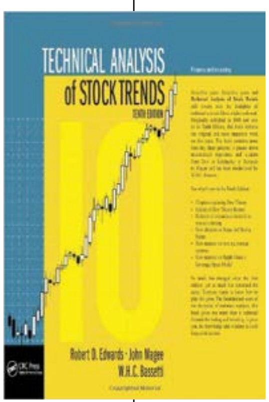
Technical Analysis of Stock Trends, Tenth Edition—By Robert D. Edwards, John Magee, and W.H.C. Bassetti

Reviewed by Regina Meani, CFTe

My introduction to technical analysis over 30 years ago occurred when someone loaned me a copy of *Technical Analysis of Stock Trends*, which I later learned to affectionately call "Edwards and Magee." I can't remember which edition it was that I first read, but later I was compelled to buy my own copy, which turned out to be the fifth edition, printed in the late 1960s.

It only came to my notice a short while ago that, after 65 years, it was in its tenth edition. Again, I was compelled to purchase a copy and see if what I had always considered to be the "bible" of technical analysis had been expanded on and, if possible, improved.

After my first reading many years ago, I did as suggested by Magee: the reader should not skim through this book and put it on his library shelf. Instead it should be read and reread and constantly referred to.[1] I advise my clients and all first time readers that they should take a chapter at a time and really absorb it before going on to the next.



I was intrigued to see what changes had been made. One of the most notable differences was the interaction between the Internet and the material in the book, meaning that the content will not be overlooked or undervalued by our 21st century obsession with everything digital. The Web links enhance the reading experience, as it allows a side-by-side visage with charts, and the links to past letters give real-time examples. Chapter 17 summarises the effect of the advances in technology and its impact on the technical analyst. Appendix B is invaluable for its resources—with links to Internet sites and further reading.

The flyleaf states that so much has changed since the first edition, yet so much has remained the same. It is to Bassetti's credit that in the three editions he has edited and co-authored, he has meticulously moved or deleted much of the content that would seem laborious and heavy to the novice but has left in place the traditional and fundamental methodology of technical analysis to remain as the essential backbone of the text.

One may ask how a book can survive 65 years in an ever-evolving and changing market environment. The answer is given in the preface to the eighth edition and lies in the answer to the quintessential technical analysis question about how chart patterns form and trend lines develop. To quote Bassetti, "Chart formations identified and analysed by the authors are graphic representations of unchanging human behaviour in complex multivariate situations. They are the depiction of multifarious human actions bearing on a single variable (price)."[2] To add another quote that I find appropriate here is from the lips of Gordon Gecko in the movie "Wall Street": "The point is, ladies and gentleman, that greed, for lack of a better word, is good. Greed is right, greed works. Greed clarifies, cuts through, and captures the essence of the evolutionary spirit. Greed, in all of its forms; greed for life, for money, for love, for knowledge has marked the upward surge of mankind."[3] While Gecko focuses on greed, his message is about human emotions, which is one of the strongest market forces powering price.

So if this text has withstood the test of time, why did it need to be updated? The text's survival into the 21st century results from Bassetti's ability to encompass the ongoing advances in technology. Furthermore, since the 1950s and 1960s, the marketplace has been flooded by a vast array of derivative and new products, and their inclusion is a welcome and necessary addition.

In conclusion, *Technical Analysis of Stock Trends* remains a must-read for everyone from the beginner to the more advanced trader and investor. It provides a comprehensive guide to the Dow Theory, and moreover, John Magee's Basing Points Procedure is presented as an alternative to the theory. Detailed explanations are provided for our basic building blocks for technical analysis—trend behaviour, pattern recognition, and stock selection. Taking things further, the text delves into the complexities of portfolio risk management and diversification and includes technical analysis in commodity, futures, and other derivative markets.

Additions to the tenth edition include replacing some of the chapters on Dow Theory; new material covering the Basing Points Procedure; more information on Stops and Moving Average Systems; and new content on Ralph Vince's Leverage Space Model.

I was pleased to note that the fifth edition (my copy) was the source for the following five updates, and it is indeed as Bassetti says, "a tribute to the clarity, style and content of the original"[4] that the majority of the text has remained unchanged. In my opinion, those of us with the earlier editions can continue to treasure them, but now valuable new material is available in the later editions. I must comment that I enjoyed the humour with which Bassetti tackled his monumental task, and I believe that I must join him in the dinosaur ranks. It is comforting to know that the traditional practises of technical analysis as found in the pages of Edwards and Magee are still being learned today.

Notes

[1] Robert D. Edwards, J. Magee, and W.H.C. Bassetti, *Technical Analysis of Stock Trends, tenth edition, CRC Press, FL, 2013, p. xx.*

[2] Ibid, p. xxiii.

[3] *Wall Street,* Twentieth Century Fox, 1987.

[4] Robert D. Edwards, J. Magee, and W.H.C. Bassetti, *Technical Analysis of Stock Trends, tenth edition, CRC Press, FL, 2013, p. xxvi.*

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Charles Bilello, CMT, is the director of research at Pension Partners, LLC, an investment advisor managing mutual funds and separate accounts. He is the co-author of three award-winning research papers on market anomalies and investing. Prior to joining Pension Partners, he was the managing member of Momentum Global Advisors and previously held positions as an equity and hedge fund analyst at billion dollar alternative investment firms. Mr. Bilello holds a J.D. and M.B.A. in finance and accounting from Fordham University and a B.A. in economics from Binghamton University. He is a Chartered Market Technician (CMT) and holds the Certified Public Accountant (CPA) certificate. Mr. Bilello is a frequent contributor to Yahoo Finance and has been interviewed on CNBC, Bloomberg, and Fox Business.

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Tom Cohen has been interested in financial markets since 2007, the year in which his savings account was entirely invested in BEL20 equities. Following investment setbacks, he started reading books and blogs on various investment philosophies. Recently completing a master's degree in business finance from Solvay Brussels School, Tom leaned towards a more technical approach after having read *Street Smarts* from Bradford Raschke and Connors. He has been trading his savings account based on his swing trading research. Mr. Cohen can be reached through LinkedIn or at tom.cohen@outlook.com.

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Kevin Hockert has been involved in the financial services industry since 1991. He is the director of portfolio strategies for Prospero Institute, Inc. (www.AskProspero.com), an investment advisory firm he founded in 2005. Mr. Hockert develops, tests, and delivers technically based quantitative investment solutions to financial advisors and portfolio managers and has developed several indicators and rules-based portfolio strategies that are designed to systematically allocate portfolios into and out of various asset classes. Mr. Hockert's innovative investment solutions are designed to save time and money, reduce subjectivity, and improve investment outcomes through the utilization of dynamic approaches to asset allocation and risk management. Mr. Hockert speaks to a variety of groups on the uses and limitations of technical analysis. He is a member of the American Association of Professional Technical Analysts and the Market Technicians Association (MTA) and has also served as a co-chair of the Minnesota chapter of the MTA.

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René Kempen was born in Hamburg, Germany, and earned B.S. degrees in mathematics and physics and an M.S. (expected September 2015) in mathematics from RWTH Aachen University. He currently works as a student assistant controlling capital investments.

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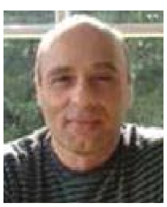
Mr. Lim is currently an analyst at Morgan Stanley in the London office. His research interests lie in asset pricing and portfolio theory, and he has written and published a number of articles in journals such as the *International Journal of Economics and Finance* and the *Journal of Finance and Investment Analysis*. He graduated with a first class honours degree in economics from University College London and holds an advanced diploma in data and systems analysis from the University of Oxford.

Stanislaus Maier-Paape



Professor Stanislaus Maier-Paape has taught mathematics at RWTH Aachen University since 2001. His specialties include differential equations, nonlinear analysis, stochastics, and applications of mathematics in other fields. Since 2010, he has been CEO of SMP Financial Engineering GmbH (www.smp-fe.de). His research fields in quantitative finance include mechanical trading systems and portfolio and money management.

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Regina Meani covered world markets as a technical analyst and associate director for Deutsche Bank prior to freelancing. She is an author in technical analysis and is a sought after presenter both internationally and locally, lecturing for various financial bodies and universities as well as the Australian Stock Exchange. Regina is a founding member and former president of the Australian Professional Technical Analysts (APTA) and a past journal director for IFTA, carrying the CFTe designation and the Australian AMT (Accredited Market Technician). She has regular columns in the financial press and appears in other media forums. Her freelance work includes market analysis, webinars, and larger seminars, advising and training investors and traders in market psychology, CFD, and share trading and technical analysis. She is also a former director of the Australian Technical Analysts Association (ATAA) and has belonged to the Society of Technical Analysts, UK (STA) for over 30 years.

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Marcin Narloch, BA, CISI, MSc, MCP, MSTA, MFTA, is a technical analyst who has been involved in the financial markets since 2009 in the capacity of a private individual. He is currently shares his experiences on his personal blog, Technical Analysis of Financial Markets (http://marcinnarloch.com), covering analysis of shares, commodities, FX, bonds, and indexes. However, ever since Mr. Narloch acquired master's degree in investment banking and securities in 2013, his true passion and main focus has been on share analysis from both the technical and fundamental sides. Being a computer programmer for over 10 years, Mr. Narloch realised he could combine his programming skills with his passion for the financial markets. In his early career in Web development, he came across Search Engine Optimisation, which provided him with invaluable insights into peoples' behaviours on the Internet. That led him to development of technical analysis strategies utilising Google search volumes and stock prices and volumes. This development culminated in a proposal of a unique technical analysis indicator as part of his most recent research paper for IFTA and earned him the MFTA designation in 2014.

Andreas Platen

Andreas Platen obtained his master's degree in mathematics at RWTH Aachen University in 2012. In addition to his interest in numerical mathematics, he started to explore the field of quantitative finance in 2010. In his research, he focused on the design of mechanical trading systems and studied technical analysis questions empirically. Currently, he is a Ph.D. student under the supervision of Professor Maier-Paape and mainly works on risk measures and money management.

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Russell Shor graduated with honours in economics from the University of South Africa. He has worked at various companies, including Macquarie Bank and Thomson Reuters. He is a private trader and makes all his investing and trading decisions based on technical signals. A stockbroker friend introduced him to technical analysis many years ago, and he has been hooked ever since. He is particularly interested in intermarket relationships, the economics thereof, and the psychology of the various market participants. Recently, his preference has moved away from a discretionary-based methodology to a more defined quantitative based system.

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