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Inside This Issue

"Weak leadership can wreck the soundest strategy; forceful execution of even a poor plan can often bring victory."
—**Sun Tzu**

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Letter From the Editor

By Dr. Rolf Wetzer, CFTe, MFTA

Dear IFTA Colleagues and Friends:

I hope that you and your family and friends came through the year healthy and safe. We are living through strange times. Something unprecedented keeps us from doing what we are used to. We shelter ourselves by staying at home, wearing masks, and restricting our meetings with others. The same applies to IFTA. For the first time in our history, there will be no in-person conference this year. We canceled Philadelphia, we will stay at home, and we will not meet as usual. Also, for the first time, there will be an online conference.

But, despite the pandemic, there is still an *IFTA Journal.* Not business as usual, but nevertheless as normal as possible. IFTA is international and so is this *Journal.* We have gathered articles and papers from colleagues around the world.

In this issue, you will find five papers from our MFTA program. Starting with the first idea until the final grading of the paper, our colleagues usually spend almost a year achieving their MFTA designation.

We also have two papers that NAAIM has kindly made available to us. NAAIM also had to cancel its annual meeting, and hence, the winner of the Wagner Award will not be announced until later this year. We therefore are publishing papers from previous years. Furthermore, we are more than happy about the long-lasting cooperation with NAAIM. I want to thank NAAIM for its support and especially Susan Truesdale for her kind cooperation.

We also have two articles from colleagues in Egypt and Japan. The authors were speakers at our last conference in Cairo. Since their presentations raised much interest, they both agreed to write an article about their respective topics to make them available for a broader audience.

Last, but not least, the *Journal* traditionally closes with a book review from our Australian colleague, Regina Meani. She is something like the faithful soul of the *Journal.* Always there, always willing to help and to support. Thank you for that.

Finally, I need to thank Aurélia Gerber for her help and especially Linda Bernetich. Without Linda and her team, the *Journal* simply wouldn't exist. Thanks for your patience and organizational skills.

I hope that you enjoy the *Journal.*

Best regards,
Dr. Rolf Wetzer, CFTe, MFTA

...the greatest resources for the Journal are our colleagues from all over the world.

Number-Based Sentiment Indicators

By Przemysław Smoliński, MFTA

Przemysław Smoliński, MFTA

Stanislawa Herbsta 2a/17
Warsaw, 02-784
Poland

+48 696 433 713
przemyslaw.smolinski2@pkobp.pl

Abstract

Depending on the stock exchange, various types of data are available to determine commitment of traders that can be used to help forecast future market behaviour. Such data may be released directly by the exchange itself or be obtained through various kinds of surveys of trader opinions and sentiment. While the former type of data is not always available, given that such data is not published by all exchanges, the latter is frequently burdened with different types of errors that arise from conducting the survey on a limited group of traders, the periodic nature of the surveys, etc. Help in solving the above problem came, rather unexpectedly, from emotionless algorithms. An investment portfolio based on them turned out to be a good indicator of market sentiment.

A detailed analysis of the above issue proved its solid theoretical foundation based on the theory of cycles and the fractal nature of the market as well as capital flows in the stock market and in the economy as a whole. More importantly, however, it also has practical investment applications. This thesis presents the theoretical foundations of the described issue and examples of its practical application.

Acknowledgements

I would like to start by thanking Paweł Małmyga for exchanging many interesting investment ideas with me and for the countless joint strategy backtests conducted on their basis. I would also like to thank Emil Łobodziński for numerous hours of inspiring conversations about the capital market, and my year-long employer PKO BP Securities for providing me with working conditions that allow me to combine my work with my passion for technical analysis.

Introduction

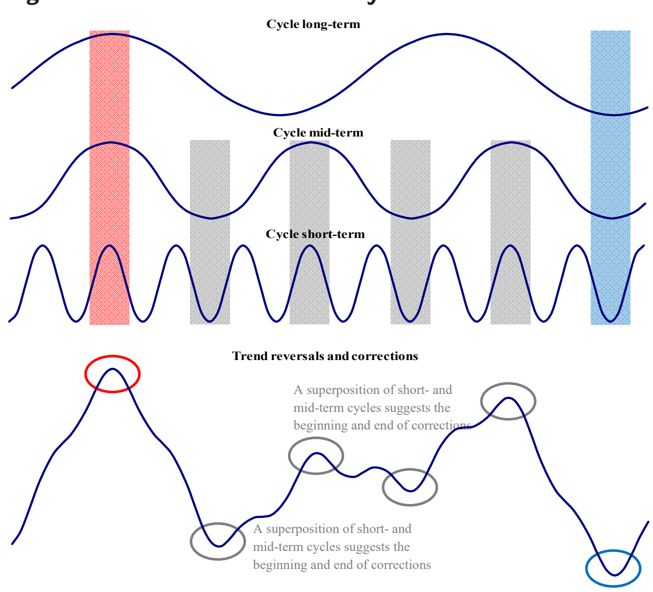
Every morning, the author of this thesis prepares an algorithmic investment portfolio covering 140 of the biggest companies listed on the Warsaw Stock Exchange. After years of monitoring signals and the general number of short and long positions in the portfolio, a pattern has started to emerge that proves helpful in determining market sentiment. As it turned out, a decisive prevalence in the number of equities on one side of the market far increases the probability of a market bottom or peak. While a gradually increasing number of rallying or declining stocks in the portfolio serves as a confirmation of the trend's strength and contributes to its continuation, a decisive prevalence of either market side serves as a reliable prognosis of a market extreme emerging and a reversal of the current long-term trend.

Based on the above observation, commitment of traders indicators, named Synthetic Sentiment Indicators, were developed. Recent years have shown that they accurately determine the probability of occurrences of market peaks and bottoms. The high effectiveness of the presented indicators can be explained from a fundamental perspective—based on the flows of capital in the economy and in the capital market itself, and from the perspective of technical analysis by using cycles and a fractal market structure.

Technical Grounds

The majority of main market peaks and bottoms can be explained by a simultaneous superposition of extremes from several different market cycles. In addition, if we consider the fractal nature of the market, where the end of the structures in various timeframes constitutes the beginning of a subsequent structure, market extremes can be forecasted on the basis of the current cycle phases in various timeframes. The simultaneous superposition of their peaks and bottoms results in the occurrence of the main market extremes.

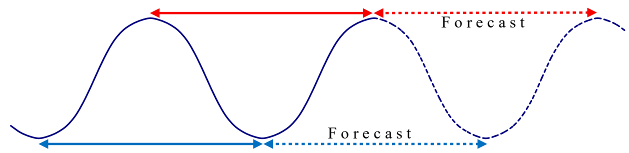
Figure 1. Interactions between cycles



Cycle Identification

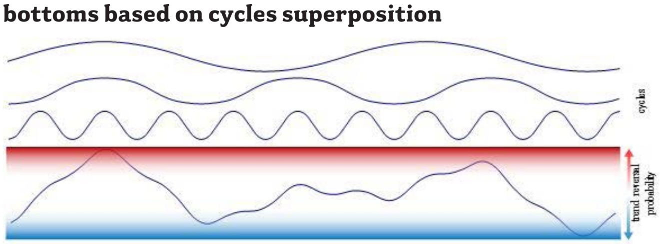
In classical technical analysis, one must first identify the dominant cycles, determine their period, and find the most recent highs and lows to predict respective market peaks and bottoms. While it may theoretically seem uncomplicated, cycle identification tends to be problematic in practice. To achieve this goal, one can use visual methods based on manually measuring the distance between visible market extremes or, alternatively, use more advanced methods, such as the Fourier analysis developed by French mathematic John Baptiste Joseph Fourier, the Phasing presented by J.M. Hurst, or the Maximum Entropy Spectral Analysis (MESA) described by John Ehlers.

Figure 2. Traditional forecasting method using cycles



While it is relatively easy to spot recurring structures on the charts during a long-time horizon, shortening the timeframe usually results in increased chaos and decreased regularity in the occurrence of market extremes. An average 54-year Kondratieff Wave, 18-year Kuznets, and 9-year Juglar cycles or the Presidential Cycle on the U.S. market can serve as a case in point here. Thanks to robust macroeconomic foundations, these cycles are relatively easy to identify, and their impact on stock prices is clearly distinguishable. However, as the cycle period is shortened, predicting market peaks and bottoms frequently becomes more difficult, and the results are prone to errors. Not only do the cycles frequently change their period and amplitude but they also tend to disappear and re-emerge after some time. Their practical application is further complicated by the superposition of several cycles of different periods and amplitudes.

Figure 3. Probability of occurrences of peaks and bottoms based on cycles superposition



In light of the above, we should consider applying a method of predicting cycle-based market extremes that is slightly different from the traditional method based on measuring the cycle period from its latest bottom or peak. If we make an assumption regarding the fractal nature of the market and the resulting occurrence of the main market extremes at the points of simultaneous superposition of the end of structures in all time horizons (a short, medium, and long investment horizon can be assumed for simplicity), we can simply restrict ourselves to determining the current position of the price in respective cycles of a specific period. As a result, instead of seeking specific cycle periods and measuring their distance from the last market extremes, we simply assume their existence and determine whether the price is currently in the growth or the decline phase. Once the phases of the studied cycles coincide, the probability of a market extreme emerging increases.

As it turns out, the approach described above works even better with respect to broad market indicators that aggregate the current cycle position for all index constituents than with regard to individual equities. For an individual stock, the convergence of cycle phases, i.e., trends with the same direction in various timeframes, may suggest a growing or declining interest in the given equities on the part of consecutive groups of traders and translate into a continuation of the current trend in the following sessions. Meanwhile, if a great majority of equities consistently remains in a growth or a decline cycle phase across all timeframes, the market can be considered widely overbought or oversold, respectively, which considerably increases the probability of a market peak or bottom emerging.

As a result, one might say that, instead of forecasting *a priori* a market extreme, in the future, it is better to focus on determining the probability of its occurrence now. The above approach can help eliminate the need for a far-from-perfect manual forecasting of peaks and bottoms or for the application of advanced mathematical methods which often do not seem fully adapted to the capital market and its constantly changing nature.

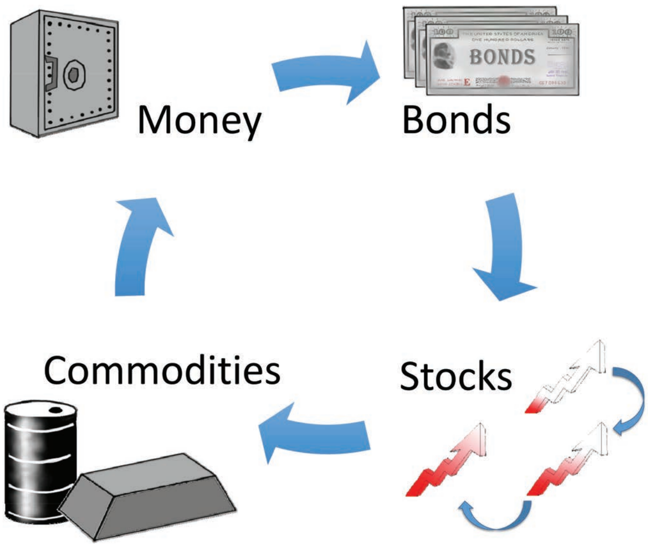
Macroeconomic Grounds

Although macroeconomics is not the focus of this thesis, every good theory should have the most extensive theoretical foundation possible. As a result, apart from the technical approach to the presented theory, we should also analyse its foundations based in the flows of capital in the economy and the capital market.

A bull market, especially supported by the good condition of the economy as a whole, means a gradual capital circulation between equities. The capital steadily flows from the rallying, overvalued stocks to less expensive ones (*e.g.,* according to peer valuation ratios) whose prices have so far been declining or moving horizontally. The higher the number of stocks following a strong uptrend, the fewer stocks that remain attractive in terms of their price, which means that, following the profit-taking from overvalued equities, the traders cannot reinvest their capital in less expensive stocks. As a result, at some point, traders begin to look for alternative means of capital allocation which, combined with changing prospects of GDP growth or the monetary policy, results in shifting the capital from the equity market toward markets that are more attractive at that time, be it commodities, money, or debt instruments. Combined with the change in the economic cycle, a strong capital outflow contributes to a reversal to downtrend on the stock market. Declining prices of equities result in a gradual increase in their attractiveness, which in time causes another inflow of capital from other areas of the capital market.

The above explanation has an additional advantage over the purely technical approach, because it also clarifies why a simultaneous superposition of cycles of the same phase and in different timeframes works better for forecasting extremes in the broad market, using all the equities comprised by the given index, than for individual equities.

Figure 4. Money flow between sectors of the economy



Materials and Methods

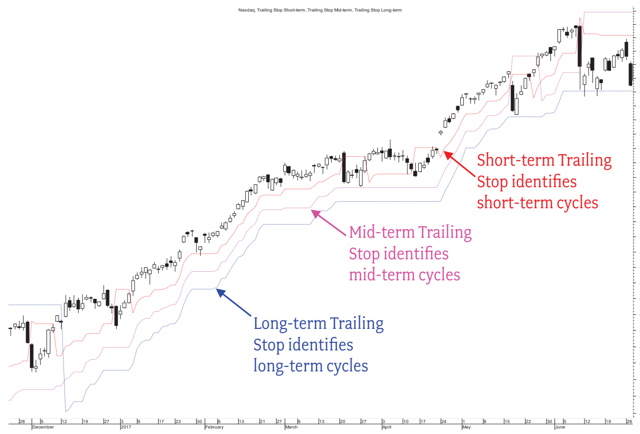
Identifying Market Sentiment

The abovementioned regularity can be used for creating Synthetic Sentiment Indicators to determine the scale of traders' commitment and, at the same time, general market sentiment that prove helpful in establishing the strength of the current trend and the degree to which the market is overbought or oversold, which is useful in forecasting the main turning points.

Given that neither the precise period of the cycles nor the exact dates of peaks and bottoms are needed, and instead are replaced with determining the current cycle phase in the adopted investment horizons, the whole process can be largely automated based on properly prepared indicators applied to the prices of all equities from the given index or market. Their combination into an aggregate indicator determines the general market sentiment.

Assuming that the cycle amplitude is largely proportional to its period, we can stipulate that the respective cycles are represented in charts by trends in various timeframes. As a result, instead of determining the phase of the cycle based on the latest bottoms or peaks, we can use classical technical analysis tools for trend determination. First, trend direction must be established for every equity separately in the short, medium, and long term. Next, the results should be summed up for the whole market or respective indices. This can be achieved through the application of many different technical analysis tools, such as the simplest moving average. In this thesis, a Trailing Stop was used, which is distant from the stock price by a fixed ATR value that increases the more the indicator is expected to serve the purpose of determining the longer cycle phase.

Figure 5. Cycle identification based on price



Given that it is possible to use classical technical analysis indicators to determine cycles instead of forecasting peaks and bottoms manually, the whole process can be automated with relative ease for a large number of equities listed on the stock exchange or included in a specific index.

Basic Interpretation

After aggregating the results for all equities included in the analysed indices, we arrive at a summary of the market in the form of indicators illustrating the current cycle phase in various timeframes that can be interpreted as a joint market sentiment of short-, mid-, and long-term traders. For most equities, the prevalence of the growth or decline phase of the analysed cycle indicates the positive or negative attitudes of the traders toward the market.

Figure 6. Various stages of market behaviour

Overbought Market

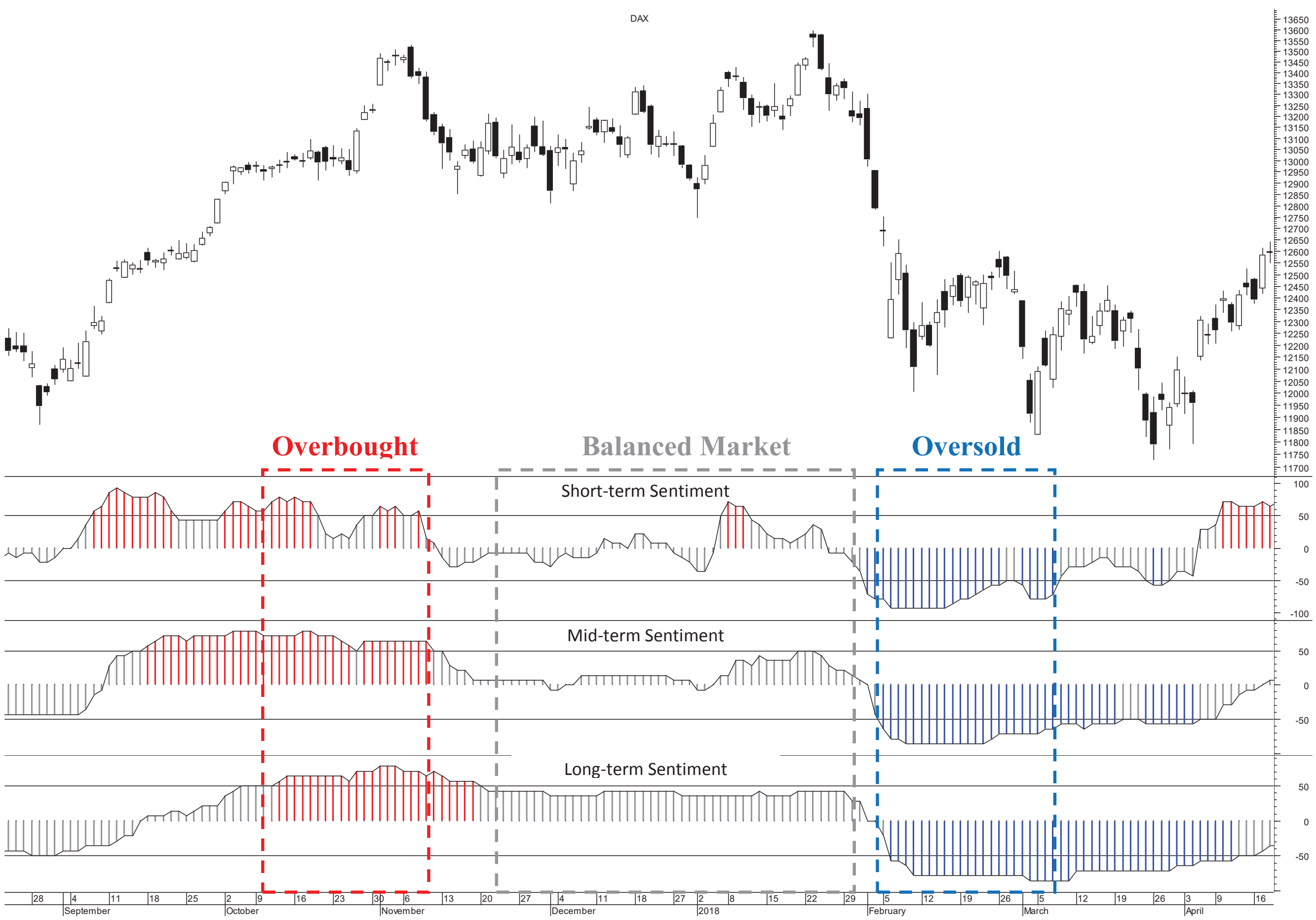
Company	Cycle term	Short- Cycle term	Mid- Cycle Long-term	Cycles Summary
1COV GY	UP	UP	UP	OVERBOUGHT
ADS GY	UP	DOWN	DOWN	
ALV GY	UP	DOWN	UP	
BAS GY	UP	UP	UP	OVERBOUGHT
BAYN GY	UP	DOWN	DOWN	
BEI GY	UP	UP	UP	OVERBOUGHT
BMW GY	DOWN	DOWN	UP	
CON GY	DOWN	UP	UP	
DAI GY	UP	DOWN	UP	
DB1 GY	DOWN	DOWN	DOWN	OVERSOLD
DBK GY	UP	UP	UP	OVERBOUGHT
DPW GY	UP	UP	UP	OVERBOUGHT
DTE GY	DOWN	UP	DOWN	
EOAN GY	UP	UP	DOWN	
FME GY	UP	UP	UP	OVERBOUGHT
FRE GY	UP	UP	UP	OVERBOUGHT
HEI GY	UP	UP	UP	OVERBOUGHT
HEN3 GY	DOWN	UP	DOWN	
IFX GY	DOWN	UP	UP	
LHA GY	DOWN	UP	UP	
MRK GY	UP	UP	UP	OVERBOUGHT
MUV2 GY	UP	UP	UP	OVERBOUGHT
RWE GY	DOWN	DOWN	DOWN	OVERSOLD
SAP GY	UP	UP	UP	OVERBOUGHT
SIE GY	UP	UP	DOWN	
TKA GY	DOWN	UP	UP	
VNA GY	UP	UP	UP	OVERBOUGHT
VOW3 GY	DOWN	UP	UP	
WDI GY	UP	UP	UP	OVERBOUGHT

Balanced Market

Company	Cycle term	Short- Cycle term	Mid- Cycle Long-term	Cycles Summary
1COV GY	UP	UP	UP	OVERBOUGHT
ADS GY	UP	DOWN	DOWN	
ALV GY	DOWN	DOWN	UP	
BAS GY	DOWN	DOWN	UP	
BAYN GY	DOWN	DOWN	DOWN	OVERSOLD
BEI GY	UP	UP	UP	OVERBOUGHT
BMW GY	DOWN	DOWN	UP	
CON GY	DOWN	UP	UP	
DAI GY	DOWN	DOWN	UP	
DB1 GY	DOWN	DOWN	DOWN	OVERSOLD
DBK GY	UP	UP	UP	OVERBOUGHT
DPW GY	UP	UP	UP	OVERBOUGHT
DTE GY	DOWN	UP	DOWN	
EOAN GY	DOWN	DOWN	UP	
FME GY	UP	UP	UP	OVERBOUGHT
FRE GY	DOWN	DOWN	DOWN	OVERSOLD
HEI GY	UP	UP	UP	OVERBOUGHT
HEN3 GY	DOWN	DOWN	DOWN	OVERSOLD
IFX GY	DOWN	UP	UP	
LHA GY	DOWN	UP	UP	
MRK GY	DOWN	DOWN	DOWN	OVERSOLD
MUV2 GY	DOWN	UP	UP	
RWE GY	DOWN	DOWN	DOWN	OVERSOLD
SAP GY	DOWN	UP	UP	
SIE GY	DOWN	DOWN	DOWN	OVERSOLD
TKA GY	DOWN	DOWN	DOWN	OVERSOLD
VNA GY	UP	UP	UP	OVERBOUGHT
VOW3 GY	DOWN	UP	UP	
WDI GY	DOWN	UP	UP	

Oversold Market

Company	Cycle term	Short- Cycle term	Mid- Cycle Long-term	Cycles Summary
1COV GY	DOWN	DOWN	UP	
ADS GY	DOWN	DOWN	DOWN	OVERSOLD
ALV GY	DOWN	DOWN	DOWN	OVERSOLD
BAS GY	DOWN	DOWN	UP	
BAYN GY	DOWN	DOWN	UP	
BEI GY	UP	DOWN	DOWN	
BMW GY	DOWN	DOWN	DOWN	OVERSOLD
CON GY	DOWN	DOWN	DOWN	OVERSOLD
DAI GY	DOWN	DOWN	UP	
DB1 GY	DOWN	DOWN	DOWN	OVERSOLD
DBK GY	UP	UP	UP	OVERBOUGHT
DPW GY	UP	DOWN	DOWN	
DTE GY	DOWN	UP	DOWN	
EOAN GY	DOWN	DOWN	DOWN	OVERSOLD
FME GY	DOWN	UP	DOWN	
FRE GY	DOWN	DOWN	DOWN	OVERSOLD
HEI GY	UP	DOWN	UP	
HEN3 GY	DOWN	DOWN	DOWN	OVERSOLD
IFX GY	DOWN	DOWN	DOWN	OVERSOLD
LHA GY	DOWN	DOWN	DOWN	OVERSOLD
MRK GY	UP	DOWN	DOWN	
MUV2 GY	DOWN	DOWN	UP	
RWE GY	DOWN	DOWN	DOWN	OVERSOLD
SAP GY	DOWN	UP	UP	
SIE GY	DOWN	DOWN	DOWN	OVERSOLD
TKA GY	DOWN	DOWN	DOWN	OVERSOLD
VNA GY	UP	UP	DOWN	
VOW3 GY	DOWN	DOWN	DOWN	OVERSOLD
WDI GY	DOWN	DOWN	DOWN	OVERSOLD



A gradual increase in the number of equities in an uptrend or a downtrend implies a strong and healthy trend that should continue until a critical value is reached. Above it, a decisive majority of equities will be at the same cycle phase in all the timeframes, which means that the whole market will be extremely overbought or oversold. If the market is overbought, the traders will not be able to reinvest their profits in cheaper equities which will result in an outflow of capital in favour of other, more attractive instruments, while stock indices will reverse to a downtrend or at least start a strong correction. On the other hand, if the market is extremely oversold, the majority of equities will be sufficiently attractive in terms of price to induce the traders to turn their back on other segments of the capital market and the indices will begin long-term uptrends.

The above description of the sentiment indicators is only basic. The indicators provide far greater analytic possibilities that make it possible to determine the current trend and signal a trend weakening, an approaching correction or a long-term trend reversal.

Structure

Synthetic Sentiment Indicators are based on four fundamental source indicators from which aggregate result indicators emerge:

- **Short-term Cycle:** determines the phase of the short-term cycle.
- **Mid-term Cycle:** determines the phase of the mid-term cycle.
- **Long-term Cycle:** determines the phase of the long-term cycle.
- **Combined Cycles:** determines the degree to which cycle phases coincide in the short, mid, and long horizons.

Each of the above indicators should be applied to every individual equity included in the index, after which the results should be summed up, giving rise to the actual Synthetic Sentiment Indicators:

- **Short-term Sentiment:** estimates the commitment degree of short-term traders.
- **Mid-term Sentiment:** estimates the commitment degree of mid-term traders.
- **Long-term Sentiment:** estimates the commitment degree of long-term traders.
- **Long vs. Short Sentiment:** estimates the degree of commitment consistency for all analysed trader groups on the long or the short side of the market.

The formulas for the above indicators can be found in the Appendix at the end of this thesis.

As stipulated above, other classical technical analysis tools can be used for constructing the aforementioned indicators, such as moving averages or oscillators. This thesis, however, uses the Trailing Stop, which determines the current trend in a specified investment horizon in a simple and transparent manner. As a result, it can easily be used for a large number of equities, while the aggregate results clearly depict the general market sentiment.

Backtests

To determine the validity of the described theory, Synthetic Sentiment Indicators were tested on several markets from 2017–2019. The test results confirmed the effectiveness of the described method for DAX, STOXX 600, ASX 200, S&P 500, and Nasdaq Composite indices; it is likely that the positive effects of its application would also apply with a high degree of probability in the case of other stock indices.

Results

The presented indicators can be applied both for the purpose of discretionary trading, in the scope of classical technical analysis, and in a systemic approach as one of many components of more complex investment strategies. In either case, the basic application of the indicators focuses on determining the current dominant market trend and its further potential and determining the points in time where the probability of the trend reversal is high.

Interpreting the Synthetic Sentiment Indicators involves aggregating the results of the three separate indicators determining the sentiment of short-, mid-, and long-term traders or aggregating the Long vs. Short Sentiment Indicator, which establishes the joint commitment of all trader groups in all investment horizons. In the former case, the basic signal of a trend reversal involves all three indicators being overbought or oversold at the same time. In the latter, a mutual position of both lines of the Long vs. Short Sentiment Indicator serves as a signal of trend continuation. Taking this into consideration, the conducted tests were divided into mean reversion and trend following. An additional third test was also performed, taking both categories into consideration.

The results of the abovementioned tests follow.

Mean Reversion

In the case of the mean reversion test, the signal reversing the current uptrend appears when all three indicators illustrating the sentiment of short-, mid-, and long-term traders are overbought (above 50 points) at the same time. The situation is reversed in the case of a sell signal that appears when all of these indicators are simultaneously oversold (below 50 points). In both cases, the position is closed automatically 10 sessions from the signal's appearance, which corresponds on average to a period of two weeks.

Table 1. Mean reversion signals

Index	Trades	Percent Profitable	Avg. Profit / Avg. Loss	Profit
ASX 200	7	86%	2.27	12.36%
DAX	12	67%	1.76	14.78%
NASDAQ	6	50%	2.97	8.98%
S&P 500	7	71%	3.43	13.63%
STOXX 600	5	80%	1.91	10.94%

Figure 7. Mean reversion signals on DAX

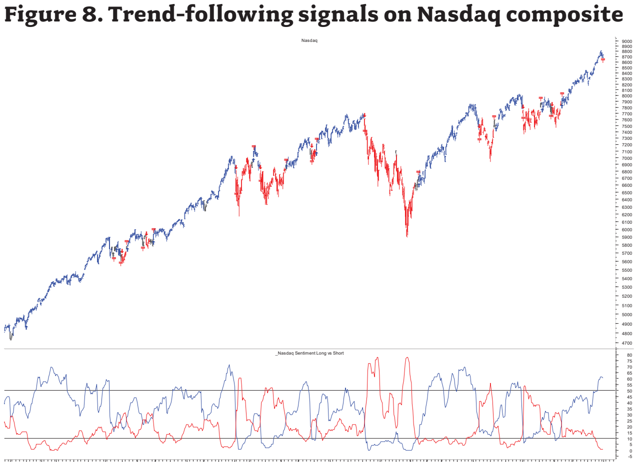
Trend Following

In the following test, trend-following signals are the result of the Long vs. Short Sentiment Indicator that illustrates the aggregate commitment of all trader groups in all investment horizons. A rally of the long line in excess of the short line generates a buy signal and vice versa. In order to filter the signals in consolidations, the signals do not appear immediately when the lines cross but, instead, when the difference between them is at least five points. The position is closed immediately after both lines cross.

Table 2. Trend-following signals

Index	Trades	Percent Profitable	Avg. Profit / Avg. Loss	Profit
ASX 200	17	29%	1.82	-5.38%
DAX	19	47%	1.97	20.46%
NASDAQ	20	40%	2.26	21.42%
S&P 500	16	50%	1.61	16.34%
STOXX 600	17	41%	1.89	6.33%

Figure 8. Trend-following signals on Nasdaq composite



Trend Following With Profit-Taking

The last test conducted combines trend-following signals with mean reversion by adding profit-taking signals to the trend-following test when either line of the Long vs. Short Sentiment Indicator enters the overbought range (above 50 points). The position is renewed after the indicator declines beneath the overbought range, provided that the original conditions for opening the position are still met.

Table 3. Trend-following signals with profit-taking

Index	Trades	Percent Profitable	Avg. Profit / Avg. Loss	Profit
ASX 200	40	55%	1.00	10.38%
DAX	32	53%	1.54	33.10%
NASDAQ	41	54%	1.27	30.65%
S&P 500	23	52%	1.51	27.73%
STOXX 600	34	50%	1.26	8.54%

Figure 9. Trend-following signals with profit-taking on S&P 500

Final Remarks on the Backtests

The results presented above illustrate the effects of a basic application of the indicators to several main stock indices. It should be noted that the indicators' parameters were not optimised with respect to generating the highest profit possible; instead, appropriate overbought and oversold levels were selected visually so that they better reflect the nature of the given market. It should also be borne in mind that the results of the tests do not illustrate any tradeable investment strategies but only the raw verifiability of the indicators themselves, which should only serve as a basis for further and more advanced works on the specific methods of their application.

Discussion

Results Commentary

The test results presented above explicitly show the high effectiveness of the Synthetic Sentiment Indicators. A positive rate of return was achieved both in the case of mean reversion signals, based on the simultaneously overbought or oversold indicators in the short, medium, and long investment horizon, and the trend-following signals that are based on the Long vs. Short Sentiment Indicator, which determines the consistency of the phases of all the cycles at the same time. In regard to the mean reversion signals, a positive rate of return was generated with respect to each of the tested indices, and the total profit amounted to 60.69%. The test of the trend-following signals returned slightly worse results; ASX 200 was the only index that generated a small loss, and the total profit for all the tested markets amounted to 59.17%.

As it turns out, a combination of both signal types generated the best results by far. Not only was a profit rather than a loss observed in the case of ASX 200, but practically all the remaining indices generated a far better result than in either test individually, achieving a total rate of return of 110.40%.

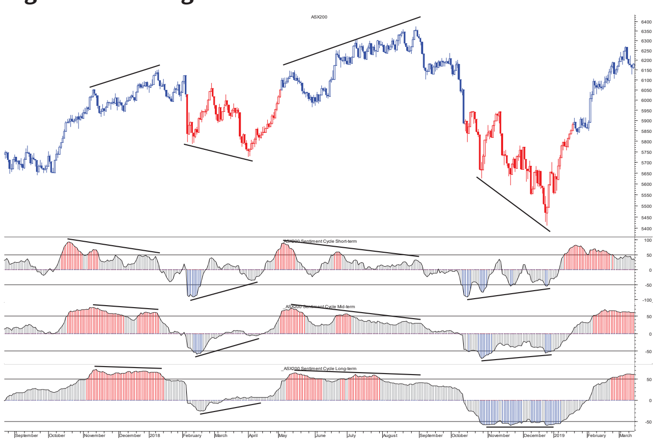
Discretionary Trading With Synthetic Sentiment Indicators

Apart from using clear and unequivocal investment signals generated by the lines of respective indicators crossing or the indicators entering overbought or oversold ranges, the Synthetic Sentiment Indicators can also be applied to a more subjective market assessment that utilizes less obvious nuances in the conduct of the indices. The mutual relations between respective indicators or their relative behaviour versus the exchange index can be used for this purpose.

Divergences

The most straightforward example of using the discussed indicators are divergences. They warn in advance of an increased probability of a correction start or a reversal of a long-term trend.

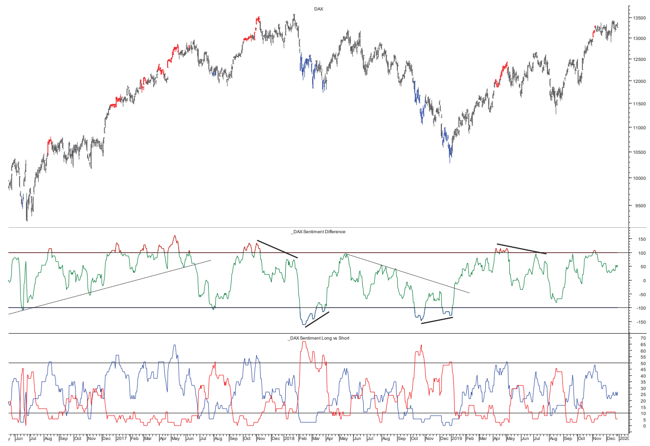
Figure 10. Divergences on ASX 200



Long-Short Difference Oscillator

The discussed indicators are not the ultimate form of presenting the collected data. On the contrary, both their presentation and interpretation merits ongoing experiments. One possibility involves using the difference between the two lines of the Long vs. Short Sentiment Indicator to create an oscillator that works better in the consolidation period while still highlighting the points of the market being strongly overbought or oversold.

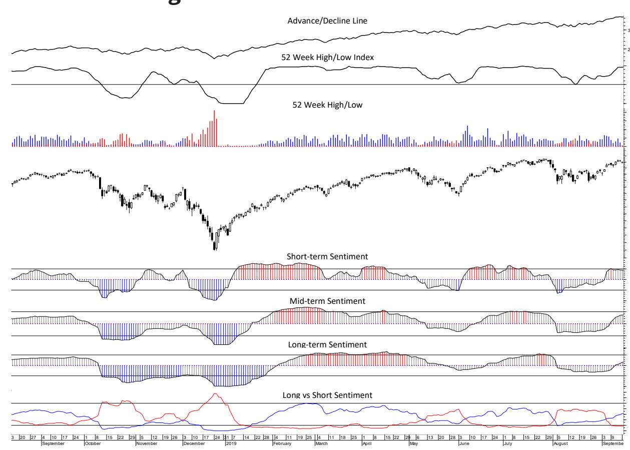
Figure 11. Long-Short Difference oscillator on DAX



Comparison With Other Broad Market Indicators

Finally, a comparison of the Synthetic Sentiment Indicators with other broad market indicators is recommended. The most popular among them are the Advance/Decline Line and the 52 Week High/Low. In a great majority of cases, the Synthetic Sentiment Indicators are decisively better with respect to disclosing a strongly overbought and oversold market and creating divergences as well as generating trend reversal and continuation signals more accurately and quickly than classic broad market indicators that are commonly used.

Figure 12. Synthetic Sentiment Indicators vs. A/D Line and 52 Week High/Low on S&P 500



Conclusion

Although, as indicated in the introduction to this thesis, the Synthetic Sentiment Indicators were developed rather by accident than as a result of purposeful studies, the tests have proved that their usefulness in determining market sentiment and forecasting (or rather estimating) the probability of market extremes emerging is very high. It also may be that the advantage of the described method involves the fact that it is the result of observing a specific market phenomenon instead of an attempt to adapt a theory to historical data. Nevertheless, irrespective of the foundations of the described indicators, they constitute a new and valuable tool in the technical analysis arsenal that permits a better determination of the current market situation than the broad market indicators deployed to date. They also help estimate the market sentiment in the case of stock exchanges that do not release data on the commitment levels of respective traders' groups, thus constituting an alternative to traders' opinion surveys. While this thesis only presents the results of applying the indicators to several selected indices, the data are promising enough, and the theory backing them is consistent enough, to support their application in other markets that are not covered by this study.

References

Ehlers, John F. *MESA and Trading Market Cycles: Forecasting and Trading Strategies from the Creator of MESA*. Wiley, 2002.

Hurst, J.M. *The Profit Magic of Stock Transaction Timing*. Prentice-Hall, 1970.

APPENDIX

Indicator Codes for Metastock

Trailing Stop Short-term/Mid-term/Long-term indicators formula:

```
Length:= 1.5; { Mid-term: 3.0 / Long-term: 4.5 }
Volatility:= Length*ATR(5);
StdevOfVolatility:= 3*(1/Sqrt(Length))*Stdev(Volatility,30);

EmaM:= (H+L+C)/3;
EmaTR:= Volatility + StdevOfVolatility;

Stop:= If( PREV < C,
If(( EmaM - EmaTR ) >= PREV,
( EmaM - EmaTR ), PREV),
( EmaM - EmaTR ));
StopLong:= Stop;

Stop:= If( PREV > C,
If(( EmaM + EmaTR ) <= PREV,
( EmaM + EmaTR ), PREV),
( EmaM + EmaTR ));
StopShort:= Stop;

If(BarsSince(C < Ref(StopLong,-1)) > BarsSince(C >
Ref(StopShort,-1)), StopLong, StopShort);
```

The following values of the *Length* parameter (illustrating the distance between the Stop Trailing line and the stock price) have been adopted in this thesis for the respective cycles:

- **Short-term:** 1.5
- **Mid-term:** 3.0
- **Long-term:** 4.5

Similarly, the relevant parameters for the **Mid-term** and **Long-term** indicators in the following indicator formulas are provided in the comment.

Short-term/Mid-term/Long-term Cycle indicators formula:

```
SignalLine:= Fml("Trailing Stop Short-term");
{ Mid-term: Fml("Trailing Stop Mid-term") / Long-term:
Fml("Trailing Stop Long-term") }

Cycle:= If(C > SignalLine, 1, If(C < SignalLine, -1, 0));

UP:= If(Cycle = 1, 1, 0);
DW:= If(Cycle = -1, -1, 0);
```

Combined Cycles indicator formula:

```
CycleShort:= Fml("Trailing Stop Short-term");
CycleMid:= Fml("Trailing Stop Mid-term");
CycleLong:= Fml("Trailing Stop Long-term");

SignalLineUP:= Max(Max(CycleLong, CycleMid), CycleShort);
SignalLineDW:= Min(Min(CycleLong, CycleMid), CycleShort);

CyclesComb:= If(C > SignalLineUP, 1, If(C < SignalLineDW, -1, 0));

UP:= If(CyclesComb = 1, 1, 0);
DW:= If(CyclesComb = -1, -1, 0);
```

To compute the target aggregate indicators, it is necessary to aggregate the result of the above indicators for all individual equities comprised by the given index. It can be achieved in three ways:

- By using the Security function for every stock price individually.
- By using the Cum function with the GlobalVars.dll add-in in Explorer.
- By exporting the values of individual indicators to an external spreadsheet and importing the aggregated value back to Metastock.

The result of the above operation should be used in the target aggregate Sentiment Indicators. It is marked by the prefix "Agg." in the formulas presented below.

Short-term/Mid-term/Long-term Sentiment Indicators Formula:

```
AdjustmentFactor:= 1 {range: 0-2};

Sentiment:= ((Agg.CycleShorttermUP*100) - (Agg.
CycleShorttermDW*(-100))) * AdjustmentFactor;
{ Mid-term: Agg.CycleMidtermUP, Agg.CycleMidtermDW
Long-term: Agg.CycleLongtermUP, Agg.CycleLongtermDW }

Sentiment.Gray:= If(Sentiment >= -50 AND Sentiment <= 50,
Sentiment, 0);
Sentiment.Blue:= If(Sentiment > 50 , Sentiment, 0);
Sentiment.Red:= If(Sentiment < -50, Sentiment, 0);

Sentiment.Gray;
Sentiment.Blue;
Sentiment.Red;
```

Long vs. Short Sentiment Indicators Formula:

```
AdjustmentFactor:= 1 {range: 0-2};

Long.Blue:= (Agg.CycleCombUP*100) * AdjustmentFactor;
Short.Red:= (Agg.CycleCombDW*(-100)) * AdjustmentFactor;

Long.Blue;
Short.Red;
```

The *AdjustmentFactor* parameter was used in aggregate indicators, as it helps adjust the given indicators to the nature of the given market. It should also be noted that the factor does not impact the manner of computing the indicator itself or its ultimate form but only permits adjusting the absolute values adopted by the indicators so that they are better adapted visually to overbought and oversold levels.

The Noise Trend

By Mohamed M. Khedr, CFTe, MFTA

Mohamed M. Khedr, CFTe, MFTA

Prime Securities
2 Wadi El Nile St., Mohandeseen, Giza, Egypt

+201550205296
M.KhedrAfifi@gmail.com

Abstract

With the various technical patterns exceeding their minimum targets, what should the optimal strategy be for dealing with such situations? And how can we reduce the risks, especially if the breakouts occurred without throwbacks or pullbacks to the neckline in the head and shoulders patterns or to the apex in the triangle patterns. This article searches for a new use of amazing Fibonacci retracements to reduce risks and looks at the possibility of anticipating peak and trough zones and identifying oversold and overbought territories after determining the target zone, especially with the development of the behavior of some players in the market recently due to many reasons, most importantly the strength of technical analysis. I will explain the impact of this development on trends and the movement of technical patterns. I will also explain how to deal with it.

Acknowledgements

I wish to express my sincere appreciation to my advisor, Dr. Rolf Wetzer, for his aspiring guidance and for his patience. I greatly benefited from his extensive experience. Also, I can't ignore the knowledge I got from the all the big financial experts, especially Professor Charles K. Patrick and Professor Thomas Bulkowski. Finally, my deep and sincere gratitude to my family for their continuous and unparalleled love, help and support.

Introduction

As it is known, the financial market experts (Kirkpatrick II and Dahlquist 2010) classified the market players into three sections: informed, uniformed and liquidity player.

They define the noise player as one who has no knowledge about evaluation norms or various analytical methods whether it is technical or financial, and also, they are the market leaders for a random movement around the equilibrium price.

How the Noise Player's Behavior Has Evolved and the Reasons Behind This

To clarify the above questions I will discuss these following six points:

The power of technical analysis

The common issue now is that this model is a head and shoulders model; however, only 50% of its composition has been completed. Therefore, this model has become the most popular among individuals. And, the interest in this pattern came after individuals ignored it, which led to great losses, to the extent that some mocked the name of the model because they didn't know the reason behind it. Besides, there is a shampoo on the market with same name. But now, after achieving impressive results on stock prices, they are showing a lot of respect to this model.

The technical reports from the various research fields have achieved remarkable results, and the ability of technical analysis to measure momentum and predict changes in price trends and technical analysis has been superior to the knowledge of financial analysis in terms of its ability to predict financial market crises if it occurs reflective analysis patterns with distant analytical targets.

All these reasons led some individual players (noise players) to pay attention and read technical reports on a daily basis to help them make decisions.

Social media networks

These networks have contributed significantly to the spread of technical recommendations that related to the market and stocks, especially with the intense competition between brokerage companies after the global financial crisis and the need to attract new clients and portfolios.

In addition, social networks have been used as an advertising and marketing method between companies by publishing brief technical recommendations that clarify the general and expected trends of stock prices in the coming period; here is where the problem showed up.

Money and fame

Some brokers and users who aren't specialized at technical analysis quoted the idea of the **mini** recommendation and applied it by creating some pages technical in nature to show various recommendations for buying and selling, which made the followers of these pages to reach thousands because the following two reasons:

1. The ease of speaking as a technical analyst and showing recommendations—all you have to do is to write the stock name, recommendation, and target (just number) without attaching a graph or an explanation about when these positions should be closed (the stop-loss level).
2. The success of this **mini** recommendation comes with the uptrend cycle, which then raises most stocks with different rates (outperforming and underperforming stocks).

And with the high salaries of the technical analysts who work at brokerage companies or funds, a lot of individuals are motivated to attend basic technical analysis courses, especially after one of the biggest securities companies at Egyptian Market hired an administrator of the pages that contain thousands of members at the company's marketing department.

The technical analyst is not a machine or a system (study and implementation)

Despite the simplicity of technical analysis in terms of study and the ease of passing and obtaining the diploma of technical analysis after a short period of focus, as well as issuing reports that contain your technical view of the market, the actual implementation and market trading is never easy because of these two reasons:

1. Disadvantage of discretionary system (overtrading, premature actions, no actions, consistent decision-making and emotions: the traders often lose money due to their emotional decisions).
2. Changing positions from buying to selling or vice versa, and the ability of the technical analyst to discipline, especially if that process will achieve a real break in his personal account (personal portfolio).

And here, I would like to refer to the definition of discipline as mentioned in the Cambridge Dictionary as "training that makes people more willing to have energy and the ability to control themselves."

So the technical analyst in his early years needs to practice and fully realize that if the rules are not followed, it will become more complicated.

Therefore, the technical analyst can classify his behavior in his first years as a noise player.

Trend is not always your friend

In order for the technical analyst to decide on the specific strategy for buying or selling, the trend must be determined, and based on this, the strategy is determined too. And so, the best strategy for the uptrend is to buy and hold, while the downtrend strategy is to sell the rebound.

In some emerging markets, such as Saudi Arabia, which does not have a tool or a mechanism of short selling, and despite the recent implementation for this tool in some Arab markets, such as the Egyptian market in 2019 and the Dubai Financial Market, Abu Dhabi and Qatar market had this license in 2017, that mechanism was not actually applied by investors for **Islamic religious reasons,** which prohibits this type of borrowing. So the trend may not be the real friend, especially during the downtrend cycle, and then some individuals adopt the buying strategy only with the steep down waves trying to make a profit in the downtrend (countertrend strategy[1]).

Each rule has an exception (interest rate vs. stock market)

With banks raising interest rates on deposits and investment certificates, investors are heading to these categories as a safe asset, away from stocks, which are a risky investment. Raising these rates will raise the cost to borrowing companies, and some of it may be moving to accelerate their expansion plans and new projects.

In the end, this will reduce the stock price that listed at the market and in turn will lead to a decline in the market and its indices, so we have two technical rules: the first one is three steps and a stumble,[2] and the second is two tumbles and a jump.[3] But each rule has an exception. I will show two examples of the positive relationship between interest rates and the stock market.

Example one—Discount rates vs. stock market in Argentina

Figure 1. Discount rate in Argentina (Source: Trading economic | Central Bank of Argentina)

Figure 1 shows that interest rates rose from 20 points to 40 points at a rise rate of about **100%** in the first half of 2016 and then tried to retest the 20 point level in 2017 and then enter into a sideway range between 20 to 40 points until July 2018. In the first half of August 2018, the interest penetrated the 40-point barrier to reach 60 points in the last half of August 2018, with an increase rate of about **50%,** and then the sharp rise wave continued to reach the level of 83 points, which was the peak formed in the second half of 2018. Then, a correction wave will start to test the 40 points in the first half of 2019.

Based on this, Argentina's unprecedented rise in interest rates from the bottom, which is created around the 20-point level in December 2015 to 83 points in the last half of 2018, which represents a **300%** rise in interest rates over the three years.

The question arises: What is the feedback of Argentina's financial market to the unprecedented rise in interest rates?

Figure 2. The monthly chart of S&P Merval (.MERV) — Index of Argentina

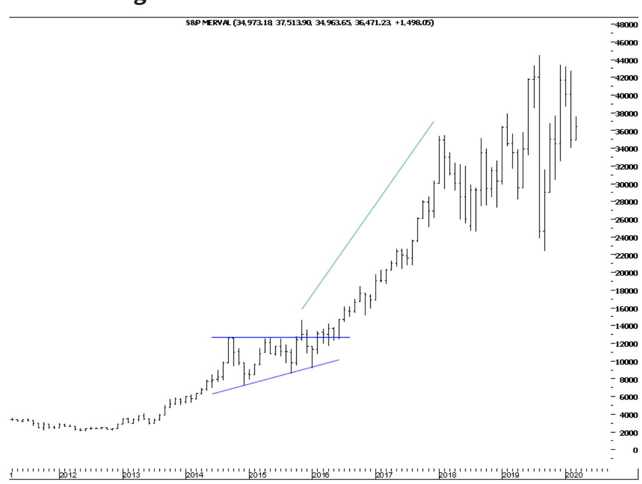


Figure 2 shows an example of the ascending triangle that was penetrated in the first half of 2016, and after that, the index direction changed from the sideway trend to the uptrend, beside its rising from the support level of 9,200 points, at which the bottom formed in January 2016, to 35,500 points at the peak, which formed in January 2018, with a rise rate about **285%** in two years.

How did that happen? The answer is the flotation (the exception) and the need to determine the real interest rate.

Figure 3. The monthly chart of USD/ARS — U.S. dollar/ Argentinean peso

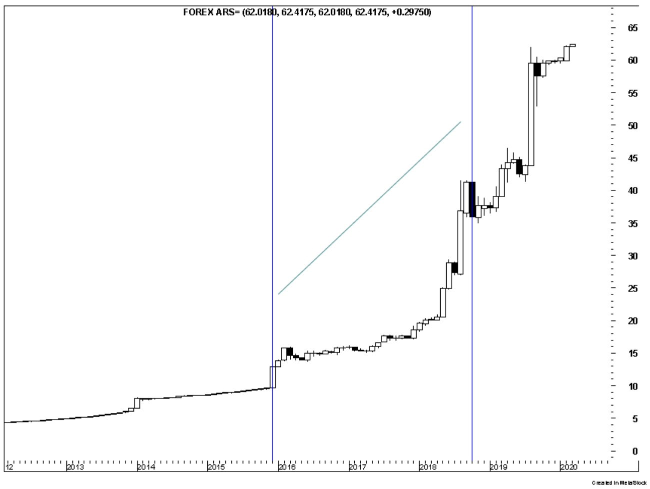


Figure 3 shows the rise of the dollar's value against the Argentine peso from 9.80, which is the bottom created in December 2015, to the peak level of 41.70 formed in the second half of 2018, with a rise rate of **325%.**

I will clarify the effect of this sharp decline in the currency of Argentina (peso) against the dollar on inflation rate.

Figure 4. The bar chart of the inflation rate in Argentina (Source: tradingeconomics.com, Instituto Nacional de Estadística y Censos (INDEC))

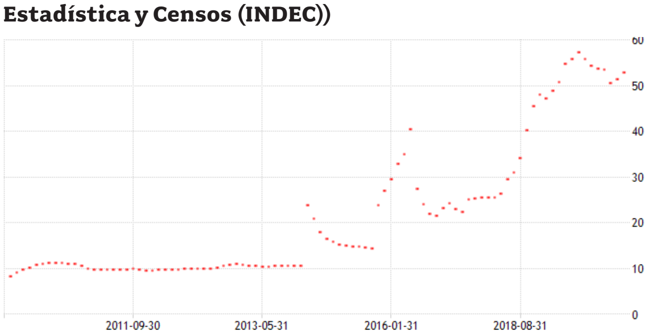


Figure 4 shows that the high rates of inflation in Argentina from the level around 15% at the beginning of 2016, reaching around 50% by the end of 2018. This means that inflation rates increased in that period by about **233%** as a result of the currency flotation decision, which in turn led to interest rates increasing and controlling inflation.

And this is why we can say that both **three steps and a stumble** and **two tumbles and jump** rules have exceptions, and the exception here is the sharp change in the currency value and the need to determine the real interest rate.

Therefore I would like to highlight more about the real interest rate, which is the rate of interest an investor, saver or lender receives (or expects to receive) after allowing for inflation. It can be described more formally by the Fisher equation, which states that the real interest rate is approximately the nominal interest rate minus the inflation rate. The real interest rate measures the compensation for expected losses due to default and regulatory changes as well as measuring the time value of money; they differ from nominal rates of interest by excluding the inflation compensation component.

For example, if an investor was able to lock in a 5% interest rate for the coming year and anticipated a 2% rise in prices, they would expect to earn a real interest rate of 3%.

How to measure:

Real interest rate = Nominal interest rate – expected inflation rate.

Example two—Discount rates vs. stock market in Egypt

Figure 5. Discount rate in Egypt (source: investing.com)

Figure 5 shows the rise in interest rates from the level of 9.75 at the end of December 2015 to reach the level of 19.25, which is the peak formed in July 2017, with an increase rate of about **97%.** And in the beginning of 2018, specifically in November, interest rates started in a correction wave to reach the level of 12.75 by the end of 2019.

Figure 6. EGX 30 index (.EGX30) – Egyptian Stock Index

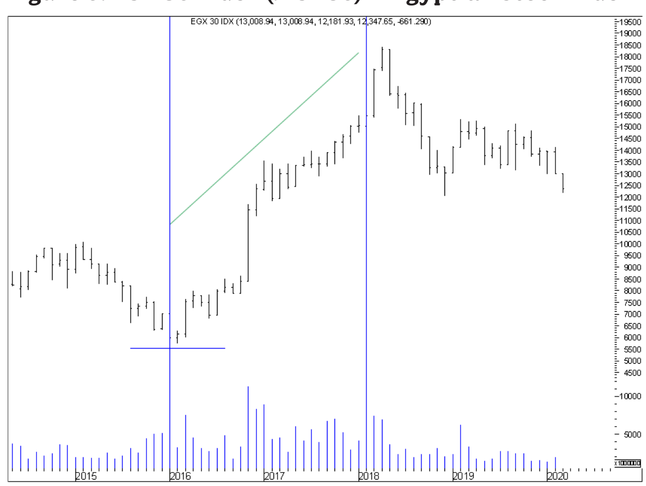


Figure 6 shows the rise of the Egyptian market index from the level of 5,550, which is the bottom formed in January 2016, reaching to the level of 15,721, which is the highest level of the index in November 2018, with a rise rate about **183%.** And despite the gradual decline of interest rates, this decline came with a violent correction wave in the index, reaching the support level of 12,000 points by the end of 2018.

Figure 7. The monthly chart of USD/EGP — (US dollar/ Egyptian pound)

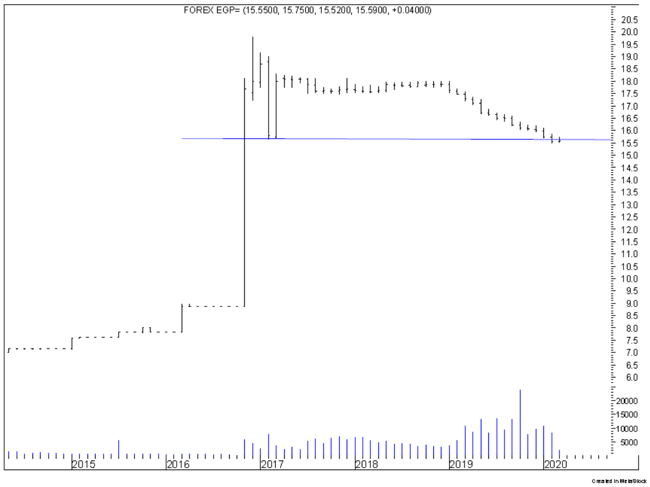


Figure 7 shows the dollar rise against the Egyptian pound from the level of 9, which is the bottom formed in November 2016 (floatation decision), to the level of 19.19, which is the peak formed by the end of 2016, with a rise rate of the dollar against the pound, which reached about 121% in two months, to appear in 2017 as a correction wave that pushed the dollar down around the level of 15.69, which is the bottom formed in February 2017.

Figure 8. The bar chart of the inflation rate in Egypt (Source: tradingeconomics.com | Central Bank of Egypt)

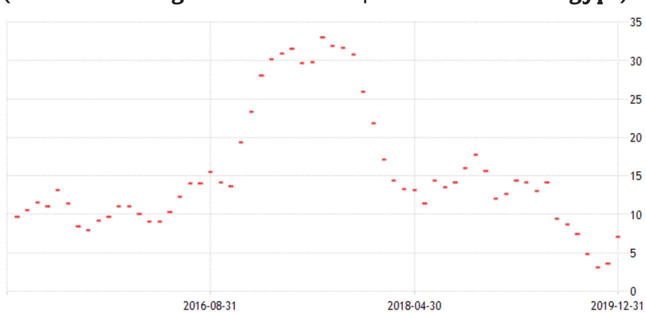


Figure 8 shows the continuation of inflation rates in Egypt from the level of 13.56 in October 2016, reaching the level of 31.916, which is the peak formed in August 2017, with an increase reached to about 135%.

Materials and Methods

This effect appears through two points: the noise trend and changes in the psychology of some technical patterns.

The Noise Trend

Definition

The noise trend is defined as resulting from a random price movement and sharp fluctuations from a series of violent uptrend waves in both the short and medium term, followed by waves of sharp downtrends, which will erase the long-term features of the main trend (more than a year). Beside this, that trend is similar in its shape and composition to the sideway trend but on a larger scale.

This trend caused sharp fluctuations in stock prices among traders, which in turn contributed to the appearance of a new kind of market trend.

In general, the oscillating trend aimed at a price that moves between support zones and other resistance and not at specific levels.

Profiting from the noise trends: Hot money stole money

In the noise trend, the hot money makes a lot of money through large-scale price movements that may reach its upward wave rates exceeding 100% during a period not exceeding two years after a sharp drop of waves that may range between 60 and 80%. I will show some historical statistics of this and the results from these examples. (See Appendix A)

Figure 9. Egyptian Transport & Commercial Services Co. SAE (ETRS.CA) — Equity in Egypt

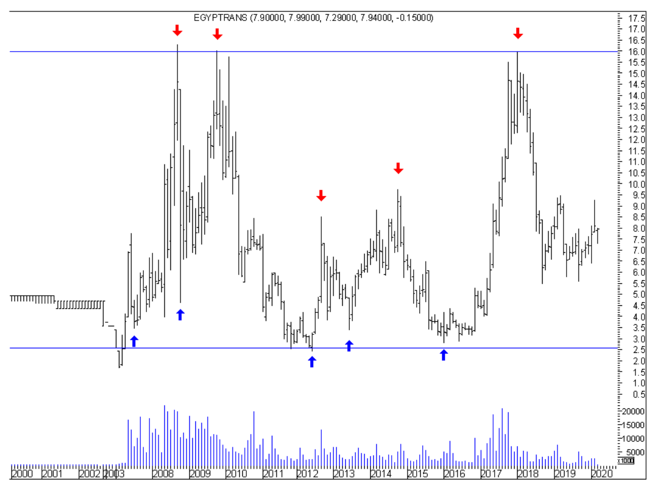


Figure 9 shows how the price has been moved between the wide range levels (2.50:16.00) during the consecutive violent waves.

Table 1. Historical statistics of the noise trend for (ETRS.CA)

The wave number	Price range	Date		Percentage (%)
		From	To	
The first violent wave	**3.47:16.27**	July 2007	September 2008	369%
The second violent wave	**16.27:4.63**	September 2008	October 2008	71.50%
The third violent wave	**4.63:16.00**	October 2008	October 2009	245.50%
The fourth violent wave	**16.00:2.43**	October 2009	June 2012	85%
The fifth violent wave	**2.43:8.51**	June 2012	September 2012	250%
The sixth violent wave	**8.51:3.41**	September 2012	June 2013	60%
The seventh violent wave	**3.41:9.74**	June 2013	October 2014	185%
The eighth violent wave	**9.74:2.80**	October 2014	January 2016	71%
The tenth violent wave	**2.80:15.96**	January 2016	January 2018	470%

Note that these violent waves were measured from the troughs (the low price) to the peaks (the high price).

Statistical results:

Frequent historical price levels produced violent upward waves (3.50-4.60-2.40-3.40-2.80), so we will consider the levels between 2.40 and 4.60 as a significant zone. On the other hand, there were historical price levels that produced sharp declining waves (16.00-8.50-10.00), so we will consider the levels between 8.50 and 16 as a significant zone.

Figure 10. Ezz Steel (ESRS.CA) — Equity in Egypt

Figure 10 shows how the price has been moved between the wide sideways range (6.00:46.00) levels during the consecutive violent waves.

Table 2. Historical statistics of the noise trend for (ESRS.CA)

The wave number	Price range	Date		Percentage (%)
		From	To	
The first violent wave	**7.42:46.36**	May 2005	February 2006	525%
The second violent wave	**46.36:14.64**	February 2006	June 2006	68%
The third violent wave	**14.64:38.45**	June 2006	April 2008	162.50%
The fourth violent wave	**38.45:5.84**	April 2008	February 2009	85%
The fifth violent wave	**5.84:26.00**	February 2009	April 2010	345%
The sixth violent wave	**26.00:3.28**	April 2010	December 2011	87%
The seventh violent wave	**3.28:19.50**	December 2011	September 2014	494.50%
The eighth violent wave	**19.50:6.11**	September 2014	January 2016	68.50%
The tenth violent wave	**6.11:30.79**	January 2016	April 2019	404%

Statistical results:

Frequent historical levels produced violent upward waves (7.50-6.00-3.00), so we will consider the levels between 3.00 and 7.00 as a significant zone. On the other hand, there were historical levels that produced sharp declining waves (46.00-38.50-19.50-31.00-26), so we will consider the levels between 19.50 and 46.00 as a significant zone.

Figure 11. Misr Chemical Industries (MICH.CA) — Equity in Egypt

Figure 11 shows how the price has been moved between the wide range levels (3.00:16.00) during the consecutive violent waves.

Table 3. Historical statistics of the noise trend for MICH.CA

The wave number	Price range	Date		Percentage (%)
		From	To	
The first wave	3.17:16.58	December 2003	January 2006	423%
The second wave	16.58:4.46	January 2006	July 2006	73%
The third wave	4.46:14.41	July 2006	May 2008	223%
The fourth wave	14.41:2.77	May 2008	October 2008	80.77%
The fifth wave	2.77:9.31	October 2008	September 2009	236%
The sixth wave	9.31:3.00	September 2009	November 2011	67.77%
The seventh wave	3.00:7.88	November 2011	June 2014	162.66%
The eighth wave	7.88:2.80	June 2014	November 2016	64%
The tenth wave	2.80:15.73	November 2016	January 2018	462%
The eleventh wave	7.88:2.81	June 2014	November 2016	64%
The twelfth wave	2.81:15.73	November 2016	January 2018	460%

Statistical results:

Frequent historical price levels produced violent upward waves (3.00-4.50), which will be considered as a significant zone. On the other hand, there were historical price levels that produced sharp declining waves (16.00-14.50-8.00-9.00), so we will consider the levels between 14.00 and 16.50 as a significant zone.

More patterns, more noise

The appearance of the patterns with targets higher than the current price intensively increases the chances of having this type of trend.

Figure 12 shows another example of the noise trend between levels of 5.50 and 42.00. Note that inside this trend there were many technical patterns, such as a triple top pattern with maximum target at the 5.50 level and counter target at the 30.50 level. After that, the stock witnessed a double bottom pattern with a maximum target at the 42.00 level and the counter target at the 17.00 level. The result is that the presence of many technical patterns can cause this type of trend.

Figure 12. El Nasr Agricultural Crops (ELNA.CA) — Equity in Egypt

How to reduce the sound of noise

The answer is to identify the zones of support and resistance based on the historical price movements and then determine the risks of trading in the direction of the price, as the risk of selling increases near the historical support areas, even if the price trend is the downtrend until this zone is violated, while the risks of buying increases near the historical resistance areas even if the price trend is the upward trend until this zone is penetrated. More confidence in the technical indicators signals related to divergences or momentum, especially that which is given near these areas of historical support or resistance. There is more reservation when the validity of penetration is tested, such as the penetration rules (3: 5%), where it is preferable to use a penetration rule of 5% in this type of trend with sharp price fluctuations to avoid the false breakouts.

The Technical Patterns

This behavior had an impact on the different technical patterns, especially the reversed trend, and its effect is divided into two parts:

1. Re-testing: It became common not to re-test the neck line in the most popular model (head and shoulders) besides the lack of return to the apex in most triangle models.
2. The Accurate Determination of Target: The lack of a careful targeting, and here I mean the maximum target, so the price can easily exceed the minimum target and at other times the maximum target. Besides the model target can be found somewhere between the minimum and the maximum target.

And now, I will show some important statistics of a financial markets expert (Bulkowski 2005), related to the most important technical patterns presented in his book *Encyclopedia of Chart Patterns.*

Table 4. General statistics in a bull market (Source: Encyclopedia of Chart Patterns, 2nd Edition)

Formations	Number of Formations	Pullback or Throwback	Average Rise or Decline (%)	Rise or Decline Over 45.00 (%)	Change After Trend End
Double bottoms, Adam & Adam	206	64.00%	35.00%	58.00 or 28.00%	-33.00%
Double tops, Adam & Adam	188	61.00%	-19.00%	9.00 or 5.00%	54.00%
Head and shoulders tops	640	50.00%	-22.00%	34.00 or 5.00%	51.00%
Head and shoulders bottoms	554	45.00%	38.00%	187.00 or 34.00%	-31.00%
Rectangle bottom	115	53.00%	46.00%	48.00 or 42.00%	-28.00%
Descending triangles	312	37.00%	47.00%	125.00 or 40.00%	-30.00%
Ascending triangle	663	57.00%	35.00%	200.00 or 24.00%	-29.00%
Symmetrical triangle	476	54.00%	31.00%	144.00 or 30.00%	-31.00%
Pennants	173	47.00%	25.00%	27.00 or 16.00%	-25.00%
Failing wedge	245	56.00%	32.00%	80.00 or 33.00%	-28.00%

Glossary explanation:

Change after trend end (See Appendix B): In the double bottom, Adams & Adam, once prices top out at the ultimate high, then what happens? They tumble about 33%. In a bear market, the decline gives up all the gains and more. For aggressive traders in a bear market, wait for prices to peak and then short the stock and ride it down.

In an analysis of this previous statistical data we found that:

1. About 50% or more of these models (head and shoulders top, head and shoulders bottom, the descending triangle and pennant) didn't rebound to the neckline or to the apex after penetration, which refers to the strategy of waiting for the throwback or pullback to buy or to add, and to short doesn't go with many technical patterns, which leads to the need for another strategy to avoid the possible unexpected throwbacks or pullbacks.
2. Amazing results from the component models, such as triangles, rectangles, and head and shoulders bottom, for which targets exceed 45%, and that is a high rate and indicates the ease of exceeding the minimum target with the possibility of exceeding the maximum of the pattern target, or that target is somewhere between the minimum and the maximum of a perfect model target.
3. When comparing the average rise or decline ratios with change after trend end ratios, we will find the following:

Table 5. Comparing the statistical results (average rise or decline/change after trend end)

Formations	Average Rise or Decline (?)	Change After Trend End (%)	Return/Risk Ratio of the Trading in the Direction of Pattern's Breakout
Double bottoms, Adam & Adam	35.00%	-33.00%	**1:1**
Double tops, Adam & Adam	-19.00%	54.00%	**1:2.8**
Head and shoulders tops	-22.00%	51.00%	**1:2.3**
Head and shoulders bottoms	38.00%	-31.00%	**1:0.80**
Rectangle bottom	46.00%	-28.00%	**1.65:1**
Descending triangles	47.00%	-30.00%	**1.56:1**
Ascending triangles	35.00%	-29.00%	**1.20:1**
Symmetrical triangles	31.00%	-31.00%	**1:1**
Pennants	25.00%	-25.00%	**1:1**
Failing wedge	32.00%	-28.00%	**1.14:1**

A. Some models, such as double bottom, head and shoulders bottom, symmetrical triangle, and pennant, with average of rise or decline target ratios are equal to the change after trend end ratios. This means that after achieving and reaching the target, the stock can witness a strong rebound that may greatly reduce the profits achieved from the target's return.

B. Another form of models like the double top and head and shoulders top which their change after trend end ratios exceeded more than the double of the average rise or decline ratios. This means that after achieving and reaching the target, the stock can witness a strong rebound that may erase all the profits achieved from the target's return.

And this indicates to the following:

1. Trend is not always your friend (sometimes the trading risks increase in the direction of the current price).
2. These models had three price targets: the minimum of target (average rise or decline), the maximum of target (rise or decline over 45%) and the counter target (change after trend end).
3. The need and importance of determining where the stock will peak or trough after the pattern breakouts to maximize profits from these patterns by benefit of the counter target.
4. The importance of managing the risks of trading in the direction of the pattern breakout, especially when the price exceeds the minimum target.

How can we reduce the risks of the counter-pattern targets using Fibonacci retracement? When is stopping trading in the direction of the breakout a must for the conservative investors?

Target Zone

The answer is to determine a target zone for each pattern where the risks of trading in the direction of the pattern's breakout are higher than the reward.

Definition

As breakouts from the support or resistance run to the next zone of support or resistance, the breakout of minimum price target in the chart patterns run to the maximum price target, which represent 100% of the previous trend wave. This gives the investors a price objective from trading below or above the minimum target while the risk is the amount that the price may go against the pattern breakout to bounce or to correct (countertrend bounce) and then risk/reward ratio can be calculated?

How to Measure?

Calculating the risk/reward ratio of trading below or above the minimum target using Fibonacci retracement:

Step number one: The return ratio below or above the minimum target is the difference between the entry price and the maximum of target divided by the entry level *100.

$$\left(\frac{\text{current price} - \text{maximum of target}}{\text{current price}}\right) \times 100$$

Step number two: The percent (38.20%) of Fibonacci retracements is used to identify a countertrend bounce from the last peak or trough within the pattern to the maximum target of that pattern.

Step number three: The risk ratio of trading in the direction of the patterns' breakout (counter target) is the difference between the minimum correction (countertrend bounce) and the entry level*100.

$$\left(\frac{\text{current price} - \text{minimum of expected rebound}}{\text{current price}}\right) \times 100$$

Step number four: Comparing the risk ratio with reward ratio to determine the target zone where the risk of correction is higher than the reward of reaching the maximum target.

Implementation

Figure 13. UAC of Nigeria PLC (UACN.LG) — Equity in Nigeria

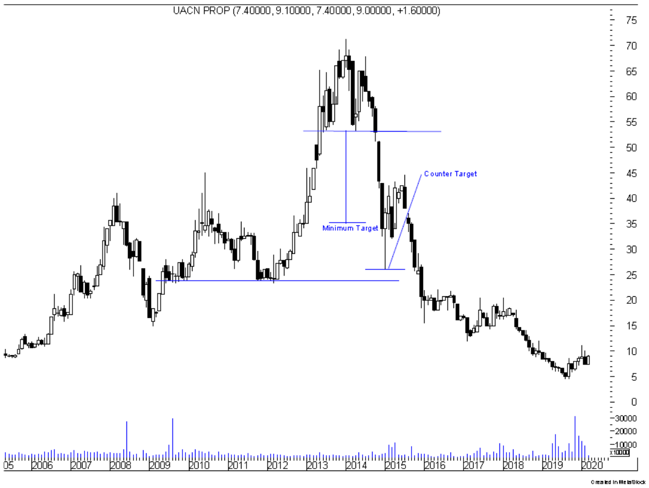


Figure 13 shows that the stock has witnessed a head and shoulders pattern; the minimum target was the level of 35.00 and the maximum target was the 24.00 level. It also shows how the price easily exceeded the minimum target at the 35.00 level to hit the 26.00 level, and then there was a strong bounce wave from it by 69% to the 44.49 level (counter target).

The processes to handle with this situation:

Based on step number one:

Calculating the reward ratios of reaching the maximum target at the 24.00 level:

Table 6. How to calculate the return ratios of reaching the maximum target

Entry Level (Short) Below the Minimum Target	Maximum Target	Return Ratio (%)
33.00	24.00	27%
30.00	24.00	20%
29.00	24.00	17%

Based on step number two:

The countertrend bounce is near the level of 40.80, which represents 38.20% of Fibonacci retracement which was taken from the distance between the last pattern's peak at the level of 68.00 and the maximum target at the level of 24.00.

Based on step number three:

Calculating the risk ratios of the bounce wave (38.20% of Fibonacci retracement), which is supposed to start from the maximum target 24.00:

Table 7. How to calculate the risk ratios of trading below the minimum target

Entry Level (Short) Below the Minimum Target	Minimum Rebound to the 38.20% of Fibonacci, Which Is Supposed to Start From Maximum Target	Risk Ratio (%)
33.00	40.80	23.63%
30.00	40.80	36%
29.00	40.80	40.68%

Based on step number four: risk/reward ratio comparison.

Table 8. Risk/reward ratio comparison of trading below the minimum target

Entry Level (Short) Below the Minimum Target	Risk Ratio (%)	Reward Ratio (%)
33.00	23.63%	27%
30.00	36%	20%
29.00	40.68%	17%

The results in Tables 7 and 8 show the increase in the risk of trading in the direction of a pattern's breakout compared to the expected return of reaching to the maximum target starting from the level of 30.00, so our target zone that helps us to reduce the risks and avoid the counter target will be between the 30.00:24.00 levels, where the stop selling is a must for the conservative investors based on the risk ratios exceeding the reward ratio.

Figure 14. Anel Elektrik Proje Taahhut ve Ticaret AS (ANELE.IS) — Equity in Turkish

Figure 14 shows the double top reversal pattern that was violated in March 2018, and it had a minimum target at 2.50 and a maximum target at 1.15. The graph also shows how the minimum target was easily broken until it succeeded in creating a bottom at 1.50 to start a quick initial bounce reached to the level of 2.05.

The processes to handle with this situation:

Based on step number 4:

Table 9. Risk/reward ratio comparison of trading below the minimum target

Entry Level (Short) Below the Minimum Target	Risk Ratio (%)	Reward Ratio (%)
2.00	9%	42.50%
1.80	21%	36%
1.60	36%	28%
1.50	45%	23%

The results in Table 9 show the increase in the risk of trading in the direction of a pattern's breakout compared to the expected return of reaching to the maximum target starting from the level of 1.60, so our target zone that helps us to reduce the risks and to avoid the counter target will be between the 1.60:1.15 levels, where the stop selling is a must for the conservative investors based on the risk ratios being higher than the reward ratios.

Figure 15. Brent Oil Futures (LCOc1) — Commodities

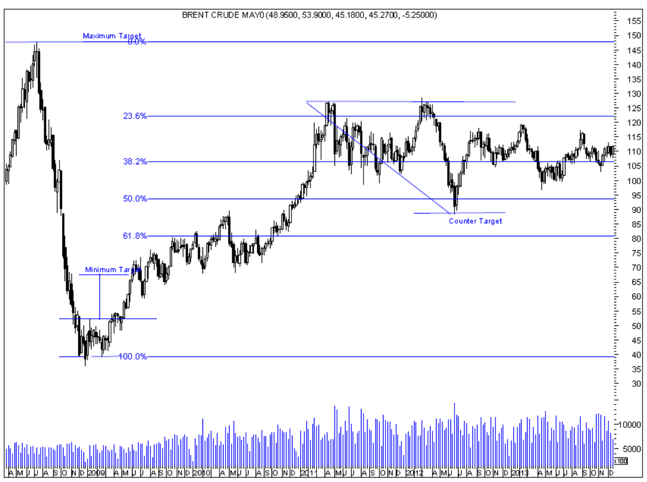


Figure 15 shows a head and shoulders bottom has been formed since March 2009 after penetrating the 50.00 barrier, and its targets were the minimum target around 68.00 and the maximum target (100% of the previous downside wave) at 147.50. The graph also shows how the price easily exceeded the minimum target to hit the level of 128.50, which is the peak formed in the month of March 2013. Then, this rally was followed by waves of decline until it reaches a level of 88.50, with a decrease by 30% from the ultimate high, which we called the counter target.

The processes to handle with this situation:

Based on step number one: Calculating the reward ratio of reaching the maximum target at the 147.50 level:

Table 10. How to calculate the return ratios of reaching the maximum target

Entry Level (Long) Abovethe Minimum Target	Maximum Target	Return Ratio (%)
90	147.50	63.88%
100	147.50	47.50%
120	147.50	22.92%
130	147.50	13.46%

Based on step number two: The countertrend bounce will be near the 106.00 level, which represents 38.20% of Fibonacci retracements (this correction ratio was measured from the right shoulder at the level of 39.00 to the maximum target at the level of 147.50).

Based on step number three: Calculating the risk ratios of the bounce wave (38.20% of Fibonacci retracement), which is supposed to start from the maximum target 147.50.

Table 11. How to calculate the risk ratios of trading above the minimum target

Entry Level (Long) Above the Minimum Target	Minimum Rebound to the 38.20% of Fibonacci, Which Is Supposed to Start From Maximum Target	Risk Ratio (%)
90	106	-
100	106	-
120	106	11.66%
130	106	18.46%

Based on step number four: Risk/reward ratio comparison:

Table 12. Risk/reward comparison of trading above the minimum target

Entry Level (Long) Above the Minimum Target	Risk Ratio (%)	Reward Ratio (%)
90	-	63.88%
100	-	47.50%
120	11.66%	22.92%
130	18.46%	13.46%

Table 12 shows the increase in the risk of trading in the direction of a pattern's breakout compared to the expected return of reaching the maximum target starting from the level of 130.00, so our target zone that helps us to reduce the risks and to avoid the counter target will be between the 130.00:147.50 levels, where the stop buying is a must for the conservative investors based on the risk ratios exceeding the reward ratios.

Figure 16. Crude oil (CLc1) — Commodities

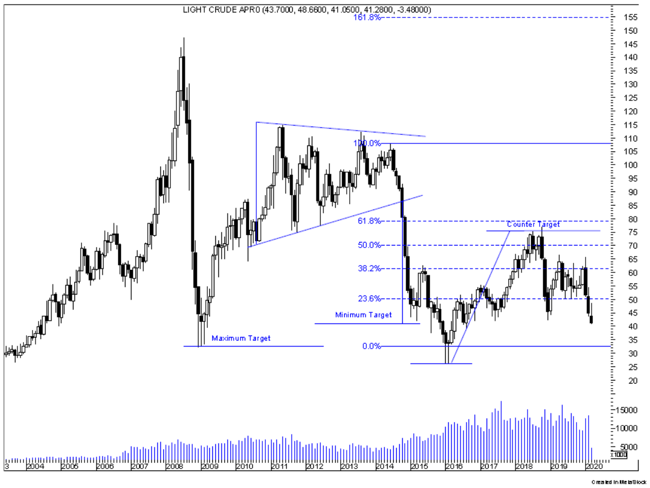


Figure 16 shows a symmetrical triangle has been formed since October 2014 after violating the support level of 85.00, and its targets were the minimum target around the 41.00 level and the maximum target (100% of the previous upward wave) was at the 32.50 level. The graph also shows how the price easily exceeded both the minimum and maximum targets to hit the level of 26.00, which is the trough formed in the month of January 2016. Then, this decline was followed by rising waves until it reached a level of 75.50, with an increase by 190% from the ultimate low, which we called the counter target.

The processes to handle with this situation:

Based on step number two: The countertrend bounce will be near the level of 61.00, which represents 38.20% of Fibonacci retracement (this correction ratio was measured from the last peak of the symmetrical pattern at the level of 108.00 to the maximum target at the level of 32.50).

Based on step number four:

Table 13. Risk/reward comparison of trading below the minimum target

Entry Level (Short) Below the Minimum Target	Risk Ratio (%)	Reward Ratio (%)
40.00	52.50%	18.75%
35.00	74%	7%

The results above show the increase in the risk of trading in the direction of a pattern's breakout compared to the expected return of reaching the maximum target starting from the level of 41.00, so our target zone that helps us to reduce the risks and to avoid the counter target will be between the 41.00:32.00 levels, where the stop selling is a must for the conservative investors based on risk ratios being double the reward ratio.

Figure 17. Copper future (HGc1) — Commodities

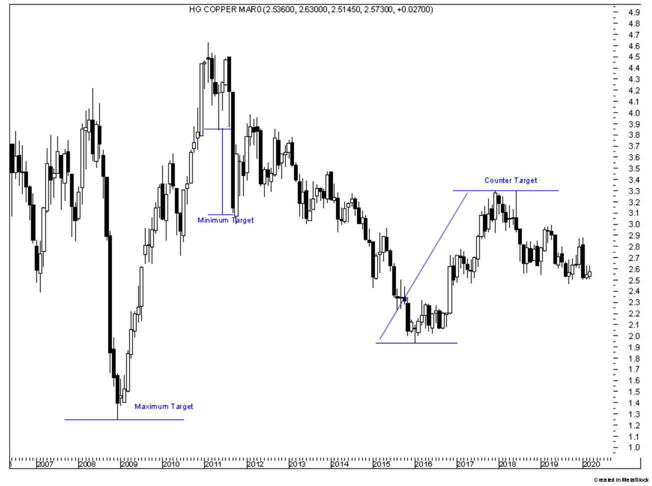


Figure 17 shows the double top reversal pattern that has been violated in September 2011, and it had a minimum target at 3.10 and a maximum target at level of 1.25. The graph also shows how the minimum target was easily broken until it succeeded in creating a bottom at 1.95 (ultimate low) to start a bounce reached to the level of 3.30 (counter target).

The processes to handle with this situation:

Based on step number two: the countertrend bounce will be around the level of 2.50, which represents the 38.20% of Fibonacci retracements (this correction ratio was measured from the second peak of the head and shoulders pattern at the level of 4.50 to the maximum target at the level of 1.25).

Based on step number four:

Table 14. Risk/reward ratio comparison of trading below the minimum target

Entry Level (Short) Below the Minimum Target	Risk Ratio (%)	Reward Ratio (%)
2.50	-	50%
2.30	8.69%	45.65%
2.00	25%	37.50%
1.90	31.58%	34.21%
1.80	38.88%	30.55%

Table 14 shows the increase in the risk of trading in the direction of a pattern's breakout compared to the expected return of reaching the maximum target starting from the level of 1.90, so our target zone which helps us to reduce the risks and to avoid the counter target will be between the 1.90:1.25 levels, where the stop selling is a must for the conservative investors based on the risk ratios being equal to or increasing more than the reward ratio.

Focus on Failure

When Does This Method Fail to Achieve Its Main Purpose of Reducing the Risk of Trading in the Direction of the Pattern's Breakouts?

From the research, we found that using this method to reduce the risk of the counter target is consistent with most cases in which the patterns did not fail because it is based on the rules and foundations of technical analysis, and they are correction ratios (Fibonacci retracement) and the risk/reward ratio, but what if the maximum target is unknown, and this is happening when the pattern's targets reaches a new historical level (all-time high)?

Puzzle 1. McDonald's (MCD) — Stock in USA

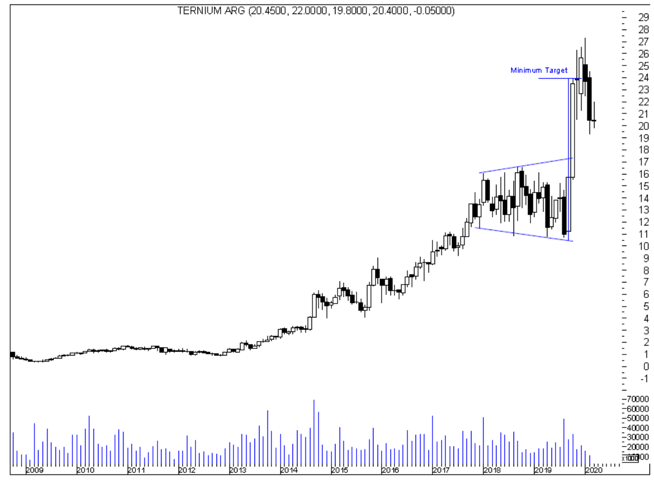
(Source: investing.com)

Puzzle 1 shows a bullish triangle pattern has been formed after penetrating the barrier at 102.00 levels with its minimum target at approximately 122.00 levels. The maximum target is unknown (the stock was moving in new historical levels).

Puzzle 2. Sociedad Comercial Del Plata (COME.BA) — Equity in Argentina

Puzzle 2 shows an ascending triangle has been formed after penetrating the resistance level of 1.95 with the minimum target at the 2.65 level, but the maximum target is unknown (the stock moved at new historical levels).

Puzzle 3. Ternium Argentina SA (TXAR.BA) — Equity in Argentina



Puzzle 3 shows that the broadening formation has been formed after breaking the barrier of 17.40 with minimum target at the 24.00 level, but the maximum target is unknown (the stock moved at new historical levels).

How to Overcome This Problem to Define Our Target Zone

The solution for these puzzles is to use the amazing Fibonacci retracements, especially the 423.00% that will be taken into consideration as a significant resistance level (maximum target), and it is calculated by taking the distance from the last peak to the last bottom within the pattern.

The Implementation

Puzzle 4. Solving the puzzle number 1 McDonald's (MCD) — Equity in USA

(Source: investing.com)

Puzzle 4 shows how the maximum target of the pattern is determined using the ratio 423% of Fibonacci retracement, especially if the pattern is at new historical levels, and it is calculated by taking the distance from the last peak at the level of 101.40 to the last bottom at the level of 87.50 within the pattern, which is in this case at the 145.00 level, which will be considered as a maximum target. Then we can find our target zone.

The process to find our target zone:

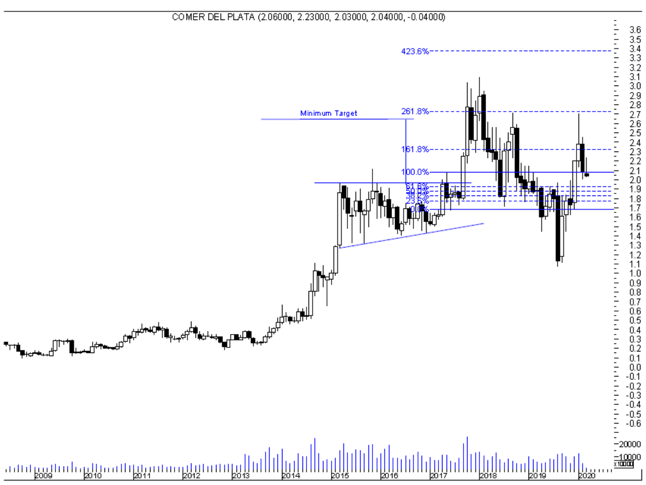
Based on step number four:

Table 15. Risk/reward ratio comparison of trading above the minimum target

Entry Level (Long) Above the Minimum Target	Risk Ratio (%) of the Expected Counter Target at 123.00 (38.20% of Fibonacci Retracement)	Reward Ratio (%) of Targeting the 145.00 Level (423.00% of Fibonacci Retracement)
125.00	1.60%	16.00%
130.00	5.38%	11.50%
132.00	6.82%	9.85%
133.00	7.50%	9.00%
134.00	8.21%	8.20%

Table 15 shows that our target zone will be between the 134.00:144.00 levels, where the reward ratios are equal to or less than the risk ratio, and the counter target or strong correction is expected to happen near this zone.

Puzzle 5. Solving the puzzle number 2 Sociedad Comercial del Plata (COME.BA) — Equity in Argentina



Puzzle 5 shows how the maximum target of the pattern is determined using the ratio 423% of Fibonacci retracement, and it is calculated by taking the distance from the last peak at the level of 2.77 to the last bottom at the level of 1.67 within the pattern, which is in this case at the 3.37 level, which will be considered as a maximum target. Then we can find our target zone.

The process to find our target zone:

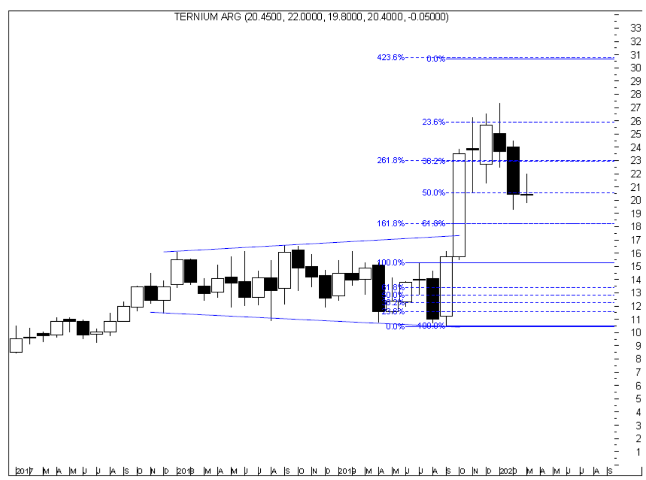
Based on step number four:

Table 16. Risk/reward ratio comparison of trading above the minimum target

Entry Level (Long) Above the Minimum Target	Risk Ratio (%) of the Expected Counter Target at 2.65 (38.20% of Fibonacci Retracement)	Reward Ratio (%) of Targeting the 3.37 Level (423.00% of Fibonacci Retracement)
2.70	1.85%	24.80%
2.80	5.35%	20.35%
3.05	13%	10.50%
3.10	14.50%	8.71%

Table 16 shows that our target zone will be between the 3.05:3.37 levels, where the reward ratios are less than the risk ratio, and the counter target or strong correction is expected to happen near this zone.

Puzzle 6. Solving the puzzle number 3 Ternium Argentina SA (TXAR.BA) — Equity in Argentina



Puzzle 6 shows how the maximum target of the pattern is determined by using the ratio 423% of Fibonacci retracement, and it is calculated by taking the distance from the last peak at the level of 15.20 to the last bottom at the level of 10.45 within the pattern, which is in this case at the 30.60 level, which will be considered as a maximum target. Then we can find our target zone.

Based on step number four:

Table 17. Risk/reward ratio comparison of trading above the minimum target

Entry Level (Long) Above the Minimum Target	Risk Ratio (%) of the Expected Counter Target at 22.90 (38.20% of Fibonacci Retracement)	Reward Ratio (%) of Targeting the 30.60 Level (423.00% of Fibonacci Retracement)
26.00	11.92%	17.69%
27.00	15.19%	13.33%
28.00	18.21%	9.82%

Table 17 shows that our target zone will be between the 27.00:30.70 levels, where the reward ratios are less than the risk ratio, and the counter target or strong correction is expected to happen near this zone.

Stock prices can go up endlessly. What will we do if the supposed maximum target (423% of Fibonacci) is penetrated? After breaking the 423%, which is considered as a strong resistance level, we will use the penetration rule of 5% for confirmation and then the stop loss has to activate (re-entry).

Results

Determining the risk/reward ratio enables us to manage the risks and in case of technical patterns that exceed the minimum target, the reward is the maximum target and the potential risks are the lowest rebound wave, which we suppose is a correction rate of 38.20% of the Fibonacci ratios, which we also assume will begin after reaching the maximum target. Ultimately, price levels where the risk is higher than the reward rate are called target zone make technical patterns more profitable for investors by taking advantage of the countertrend.

Discussion

As for the two rules (two tumbles and jump and three steps and a stumble), we should clarify how effective and important these rules are in developed markets. For emerging markets, where currency rates are changing dramatically and where inflation rates are affecting them, there is an urgent need to determine the real interest rate and the real inflation rate as well. There are some countries that do not give real data on annual inflation rates so as not to stir up public opinion, especially when the government makes difficult economic reforms to the people, as they take a long time to show their results.

Conclusion

The strength of technical analysis and its spread among dealers had a significant impact on price movement, especially in emerging markets, which in turn led to the creation of a new type of trend whose waves are characterized by violence. This made it difficult to accurately determine targets (maximum targets) in the more common technical patterns, and this arranges the difficulty of calculating the return/risk ratio of the trade in the direction of the pattern breakouts, especially if the price exceeds the minimum target. Technical analysis did not leave anything. Fibonacci retracements were the effective tool to overcome the violent price movements. The 38.20% of Fibonacci retracements is used as a trailing stop to determine the target zone, while the ratio of 423% is used to find the unknown maximum target. The target zone has become an urgent necessity recently because it supports reducing the risks, which is a major goal of technical analysis, and not only to maximize profits.

References

Bulkowski, Thomas N., Encyclopedia of Chart Patterns. New Jersey: Wiley 2 edition, 2005.

Kirkpatrick II, Charles D. and , Julie R. Dahlquist, Technical Analysis: The Complete Resource for Financial Market Technicians. New Jersey: FT Press, 2010.

Notes

1 **A countertrend strategy** is a trading method that attempts to make small gains by trading against the current trend. Traders also refer to the practice as countertrend trading.

2 **Three steps and a stumble,** which states that "whenever the Federal Reserve raises either the federal fund target rate, margin, requirement or reserve requirements three consecutive times without a decline, the stock market is likely to suffer substantially."

3 **Two tumbles and jump,** which is based on looking for two consecutive declines, or tumbles, in the federal fund target rate and reserve requirements, and then the stock market rises. But every rule has an exception.

Software and Data

All Data obtained from MetaStock Version 17.1.1932602, and I would like to thank each of the sites (Investing.com & Tradingeconomics.com).

Appendices

Appendix A

Figure of Access Bank (ACCESS.LG) — Equity in Nigeria

The monthly chart above is another example of a noise trend (similar to a sideways trend), which was moving between the levels of 4.00:12.50. To reduce this sound of noise, it is necessary to identify the support area, where the selling risks increase, and the resistance zone, where the buying risks increase, from the historical price movements of the stock.

Appendix B

Table for Explanation (Source: Encyclopedia of Chart Patterns, 2nd Edition)

Formation	**Explanation** (Throwbacks OR Pullbacks and change after trend end)
Double Bottoms, Adam & Adam	*Since a **throwback** occurs **64%** of the time in a bull market, you can initiate a position after the throwback is complete or add to your position. ***Change after trend ends.** Once prices top out at the ultimate high, then what happens? They tumble about **33%**. In a bear market, the decline gives up all the gains and more. For aggressive traders in a bear market, wait for prices to peak then **short** the stock and ride it down.
Double Tops, Adam & Adam	***Change after trend ends.** Once a price reaches the ultimate low, it soars by climbing **54%** in a bull. Thus, if you can determine when the price trend changes from down to up, buy.
Head and shoulders tops	***Change after trend ends.** After a price reaches the ultimate low, it soars, climbing 51% in a bull market. If you can determine when the trend changes, then buy the stock and hold on.
Head and shoulders bottoms	***Change after trend ends.** After a price reached the ultimate high, it tumbled by over 30%. That behavior is a good reason for selling buy-and-hold positions.
Descending triangles	***Change after trend ends.** Once a price reaches the ultimate high or low, what happens? For upward breakouts, prices tumble about 32%, on average. Thus, if you can determine when the price has changed, even if you are late, you can still profit from it.

Determination of Time Target Zones for Price Targets of Classic Price Patterns

By Momen Atef El Shayal, CFTe, MFTA

Momen Atef El Shayal, CFTe, MFTA

SIGMA Capital
37 Gameat El Dowal El Arabeya Street
Mohandessinm, Giza 12411
Egypt

+201202257088
momen.elshayal@gmail.com

Abstract

With the claim that it is possible to begin to scientifically answer the difficult question of how long it takes to get this potential profit, this paper came to uncover a new dimension of some classic price patterns that reflect information about the approximate duration within which their price targets are expected to be achieved.

A new method that uses concepts of linear regression, and the standard deviation is introduced here to determine time target zones for the traditionally determined price targets of classic price patterns.

Seven classic price patterns were tested to prove the thesis. They include double top (and bottom); triple top (and bottom); bullish and bearish: rectangle; ascending triangle; descending triangle; symmetrical triangle; and head and shoulders.

I believe that if we could get such information, we can make more effective and well-planned investment decisions and it will be much easier to choose from various coinciding trading opportunities.

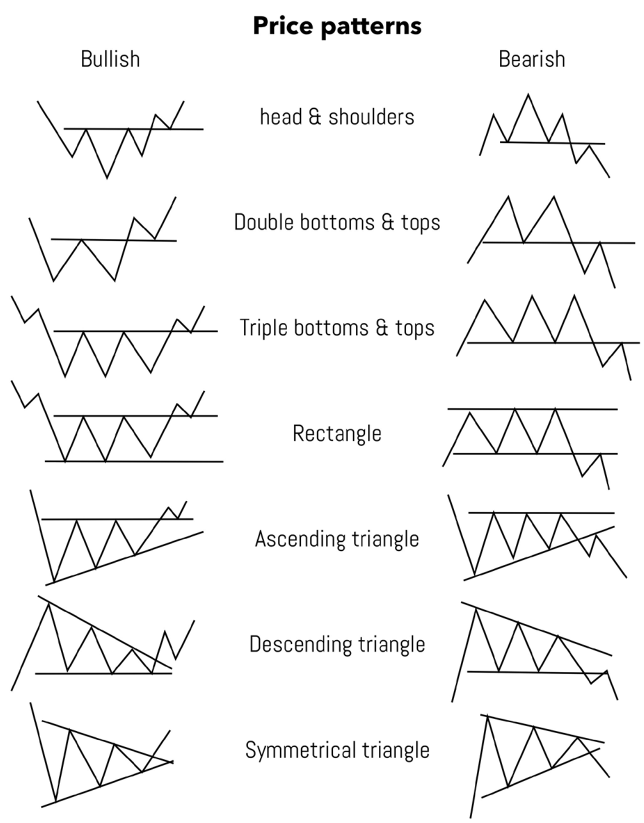
Introduction

In fact, most, if not all, efficient investment decisions are taken after answering two main questions; the first is how much is the expected return? And the second is how much time is expected to get that return? Since the decision to invest in financial markets should be an efficient one, it needs to be supported by information about the expected time that is required to earn an expected return. At the same time, most technical analysis theories focus on studying price action to determine future price targets; however, they don't focus with the same degree on determining the time targets of these price targets.

For instance, classic price patterns are a cornerstone in the body of technical analysis; they reflect how history repeats itself throughout frequent battles—based on fear and greed—between buyers and sellers. These battles appear on charts as recognizable repetitive sideways price patterns, and an easy minimum price target can be determined once a price breakout occurs by measuring the largest vertical distance between the pattern's boundaries and projecting it from the breakout point. So far it is good, but what about the time it takes to achieve this price target?!!

Actually, there are a lot of classic price patterns with different degrees of fame. Some books, such as *Technical Analysis of Stock Trends* (Edwards, Magee and Bassetti) and *Trading Classic Chart Patterns* (Bulkowski), tried to explain them in details; others, like *Technical Analysis of Financial Markets* (Murphy), *Technical Analysis Explained* (Pring), and *Technical Analysis: The Complete Resource for Financial Market Technicians* (Kirkpatrick and Dahlquist), tried to simplify them; moreover, others, like Encyclopedia of Chart Patterns (Bulkowski) tried to collect most of them. Although some of the classic price patterns can be categorized as reversal patterns and others can do a dual job as reversal and continuation patterns, in this paper, they were categorized as bullish and bearish ones according to the breakout direction (Figure 1).

Figure 1. Bullish and bearish price patterns

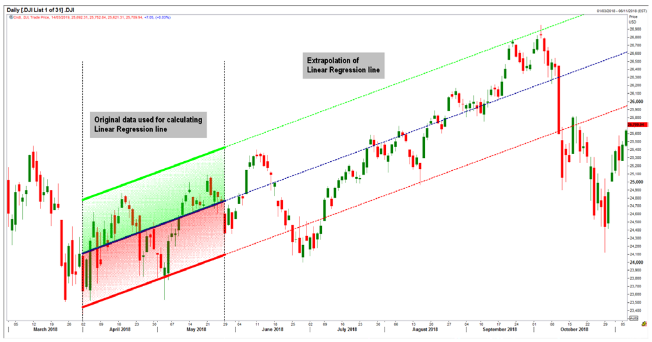


On one side, theoretically, the last price swing in the price pattern represents the beginning of imposing control from the warrior who finally wins the trading battle. So, the focus on the last price swing can certainly reveal something worthy about the remaining power of the victor.

On the other side, the flashing sentence that Perry J. Kaufman included in the 5th edition of his book *Trading Systems and Methods*—"A time series is not just a series of numbers, but ordered pairs of price and time."—made me think about the fact that we already have two axes (price and time), and completed classic price patterns enable us to determine a future point on the price axis, so there must be a way to get the opposite point on the other axis (the time axis).

After gathering all together with the aid of a simple statistically based tool, which is the standard deviation channel, a new method for determining time target zones of the price targets generated by classic price patterns is introduced here.

Figure 2. Standard deviation channel



The standard deviation channel (which is included in most charting programs) is also alternatively referred to as the linear regression channel. And as the name implies, it consists of two standard deviation bands above and below an x-period linear regression line (Figure 2).

In origin, this price analysis' tool is used for identifying the price trend and the standard deviation bands usually act as support and resistance levels and are used for trading purposes, by the way. However, in this paper, it is used differently.

Theoretically, the linear regression is a statistical tool that is used to find a linear relationship between two variables (X and Y), which enables one to find the value of Y (the dependent variable) for each value of X (the independent variable), and in the case of Price and Time, we can find the value of time for the value of a specific price. It uses the least-squares method to plot a straight line through data to minimize the distances between the actual data and the resulting line, and to find the best straight-line fit, the following formula is used: $\hat{y} = b(x) + a$

Where [$\hat{y}$] is the predicted value, [b] is the slope, and [a] is the y-intercept (the value of y when x = 0).

A distinct advantage of linear regression is that it can forecast future price movement by simply extending the resulting straight line. If we can consider that the regression values give the mean over the calculation period, then the forecast is an extension of the mean.

Besides, the bands of the standard deviation channel are plotted to determine the approximate range of the dispersion of price movements around the regression line. By default, the standard deviation bands are set to two as according to the normal distribution; 95% of the observations lie within two standard deviations of the mean.

By applying the standard deviation channel tool on the last swing of the price pattern and extend it straight forward; we can assign a time target zone for the assigned price target of the completed price pattern.

Materials and Methods

Data and Period of Investigation

To test the thesis presented in this paper, daily historical data of three different liquid financial markets from January 2008 until December 2018 was examined. It should also be noted that all price data used throughout the paper were obtained from Reuters.

The financial markets that were examined are:

- Equity market (S&P 500)
- Commodity market (Light crude oil)
- Currency market (EUR/USD pair)

Here, I've chosen seven famous classic price patterns—head and shoulders, double bottoms and tops, triple bottoms and tops, rectangle, ascending triangle, descending triangle, and symmetrical triangle—and extracted them manually from daily charts of the three aforementioned instruments. The period of investigation from January 2008 until December 2018 was selected, as it included a great variety of up and down trends and nearly witnessed all market conditions where plenty of classic price patterns could be captured.

Types of Completed Price Patterns

In theory, classic price patterns can't be considered as completed ones until an actual price breakout occurs. Further, prices usually react in one of two certain ways after the breakout. Either a pullback movement to the broken boundary of the completed price pattern will occur before achieving the price target or prices will continue directly toward the target of the pattern.

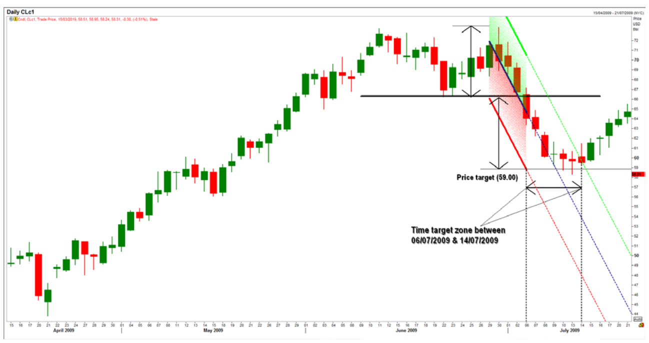
In this section, I will explain the method of determining the time target zone for the price target of a completed price pattern in each case. Also, it should be mentioned that this method can be applied to six of the seven price patterns that are examined in this paper exactly in the same way; however, the head and shoulders price pattern is considered a special case, which will be also explained later in this section.

Completed Price Patterns Without Pullback Movement After the Breakout

We can determine a time target zone for the price target of a completed price pattern that isn't followed by a pullback movement to the broken boundary once a price breakout occurs by plotting the standard deviation channel on prices starting from the lowest day in the last price swing before the actual bullish breakout till the breakout day then extend the channel to the right (Figure 3). The time target zone is the period between the two vertical lines projected from interception points of the price target level and the bands of the extended standard deviation channel. The opposite is true in the case of bearish breakouts (Figure 4).

Figure 3. The time target zone for the price target of a completed bullish price pattern without a pullback movement

Figure 4. The time target zone for the price target of a completed bearish price pattern without a pullback movement



Completed price patterns followed by pullback movements after the breakout

If a pullback movement to the broken band of the completed price pattern followed the actual breakout, we should add this piece of data to the measurement. The standard deviation channel should be started from the lowest day of the last price swing before the breakout (or the highest day in case of bearish breakouts) until the last day in the pullback movement after the breakout, and then extend the channel to the right (Figures 5 and 6).

Figure 5. The time target zone for the price target of a completed bullish price pattern followed by a pullback movement

Figure 6. The time target zone for the price target of a completed bearish price pattern followed by a pullback movement

The special case of head and shoulders price pattern

The head and shoulders price pattern has a special measuring criterion. In bullish cases, the standard deviation channel should start from the lowest day of the pattern (the head) until the breakout day or the last day of the pullback movement that follows the breakout. The opposite is true in bearish cases (Figures 7 and 8).

Figure 7. The time target zone for the price target of bullish H&S price pattern without a pullback movement

Figure 8. The time target zone for the price target of bearish H&S price pattern followed by a pullback movement

Examples From Various Financial Markets

Double bottom and double top price patterns

Figure 9. Credit Agricole bank (CAGR.PA)—Daily

An example from the French stock market is shown in a daily chart of Credit Agricole bank (Figure 9). After finishing a double bottom price pattern then a pullback movement to the middle peak, the price target of the pattern was achieved later on within the determined time target zone between August 18, 2012, and September 14, 2012.

Figure 10. Jazira bank (1020.SE)—Daily

Figure 10 shows a case of a double bottom pattern without a pullback movement that occurred in a daily chart of the Jazira bank in the Saudi stock market. The price target of the pattern was achieved within the determined time target zone between December 13, 2017, and January 28, 2018.

On the other hand, Figure 11 shows a completed double top price pattern, which is followed by a pullback movement in the Silver. Subsequently, the price hit the target of the pattern within the determined time target zone between October 18, 2012, and November 6, 2012.

Figure 11. Silver (XAG=)—Daily

Figure 12. Itau Unibanco holding (ITUB4.SA)—Daily

From the Brazilian stock market, Figure 12 shows a daily chart of Itau Unibanco holding, which spotted another double top price pattern, but this time without a pullback movement. The price target was also achieved within the determined time target zone between November 26, 2010, and December 20, 2010.

Triple bottom and triple top price patterns

Figure 13. JPY (JPY=)—Daily

Figure 14. Light crude oil (CLc1)—Daily

Figure 13 shows a case of a triple bottom price pattern followed by a pullback movement that appeared in a daily chart of the Japanese Yen. Again, the price target of the pattern was achieved within the determined time target zone between November 15, 2012, and January 12, 2013.

Figure 14 shows a daily chart of the light crude oil which illustrates a triple bottom pattern without a pullback movement followed by a minimum target that was achieved within the determined time target zone between January 2, 2013, and January 25, 2013.

Here in Figure 15, a triple top price pattern appeared in a daily chart of the Gold followed by a pullback movement afterward; the minimum target of the completed pattern was achieved within the determined time target zone between June 20, 2018, and September 19, 2018.

Figure 15. Gold (XAU=)—Daily

From the London stock market, Figure 16 shows another triple top price pattern without a pullback movement appeared in a daily chart of Barclays PLC. The price target of the completed price pattern was achieved later on within the determined time target zone between October 28, 2009, and November 16, 2009.

Figure 16. Barclays PLC (BARC.L)—Daily

Bullish and bearish rectangle price patterns

The GBP pair daily chart shows a bullish continuation rectangle price pattern followed by a pullback movement (Figure 17). The price target of the completed price pattern was hit subsequently within the determined time target zone between December 10, 2013, and January 31, 2014.

Figure 18 shows another bullish rectangle price pattern, but this time without a pullback movement. It was spotted in a weekly chart of Deutsche Bank which is traded in the German stock market. Here again, the price target of the pattern was hit within the determined time target zone between April 24, 1998, and July 24, 1998.

Figure 17. GBP (GBP=)—Daily

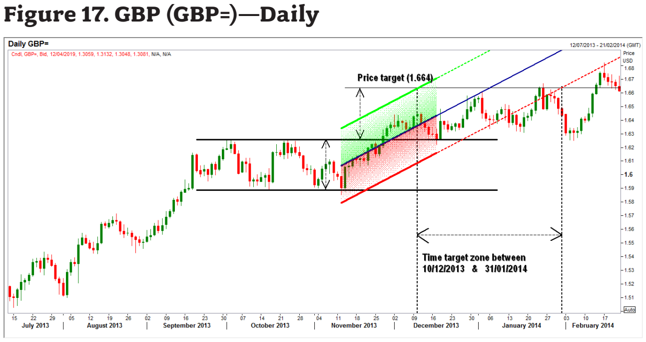


Figure 18. Deutsche Bank (DBKGn.DE)—Weekly

In another example from the London stock exchange, Figure 19 shows a bearish rectangle price pattern followed by a pullback movement. The weekly chart of the Anglo-American stock illustrates that the price target of the completed price pattern was achieved later on within the determined time target zone between February 20, 2015, and November 20, 2015.

From the French stock exchange, an example of a bearish rectangle price pattern without a pullback movement is shown in Figure 20. The daily chart of Danone shows that price target of the completed price pattern was hit within the determined time target zone between February 8, 2018, and February 28, 2018.

Figure 19. Anglo American (AAL.L)—Weekly

Figure 20. Danone (DANO.PA)—Daily

Bullish and bearish ascending triangle price patterns

The weekly chart of the Canadian Dollar pair (Figure 21) shows an example of a bullish ascending triangle pattern followed by a pullback movement. The price target of the pattern was hit within the determined time target zone between September 26, 2008, and January 16, 2009.

Figure 21. CAD (CAD=)—Weekly

Figure 22. Ten-year treasury notes (TYc1)—Daily

Figure 22 shows a ten-year U.S. treasury notes daily chart, which spotted a bullish ascending triangle price pattern that wasn't followed by a pullback movement. After finishing the price pattern, the minimum price target was achieved within the determined time target zone between November 2, 2001, and November 14, 2001.

In Figure 23, an example of a bearish ascending triangle price pattern followed by a pullback movement was spotted on a daily chart of General Electric Company's stock, which is traded in the New York stock exchange. The target of the completed pattern was hit within the determined time target zone between March 12, 2001, and March 23, 2001.

Figure 23. General Electric Co. (GE.N)—Daily

Figure 24. Bank of America (BAC.N)—Daily

Also, from the New York stock exchange, Figure 24 shows a daily chart of Bank of America's stock, which captured a bearish ascending triangle price pattern without any pullback movements; its target was hit within the determined time target zone between April 2, 2018, and April 19, 2018.

Bullish and bearish descending triangle price patterns

Figure 25. Ten-year U.S. treasury notes (TYc1)—Daily

Another daily chart of the ten-year U.S. treasury notes (Figure 25) shows a bullish descending triangle pattern followed by a pullback movement, and the minimum target of the pattern was achieved within the time target zone between August 26, 1998, and November 6, 1998.

Figure 26 shows a daily chart of Tadawul all shares index that captures a bullish descending price pattern without a pullback movement. The price target of the pattern also was achieved within the determined time target zone.

In Figure 27, a bearish descending triangle price pattern, which is followed by a pullback movement, was spotted in an hourly chart of the Euro pair. Here again, the price target of the completed pattern was hit within the determined time target zone.

Figure 26. Tadawul all shares index (.TASI)—Daily

Figure 27. EUR (EUR=)—Hourly

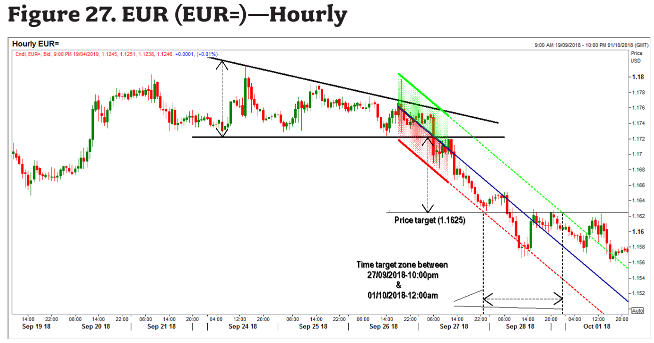


Figure 28. CHF (CHF=)—Daily

The last example of descending triangles was a bearish one without a pullback movement that was captured in a daily chart of the Swiss Franc pair (Figure 28). One more time, the price target of the pattern was hit within the determined time target zone.

Bullish and bearish symmetrical triangle price patterns

Figure 29. Commercial International Bank (COMI.CA)—Weekly

Figure 30. Ezz Steel (ESRS.CA)—Weekly

From the Egyptian stock market, a case of a bullish symmetrical triangle price pattern appeared in a weekly chart of the Commercial International Bank (Figure 29). After a pullback movement to the cleared boundary of the pattern, the price trusted and hit the price target within the determined time target zone between December 26, 2013, and June 5, 2013.

Another case from the Egyptian stock market is in a weekly chart of Ezz Steel's stock, which shows a bullish symmetrical triangle price pattern and its price target that was also achieved within the determined time target zone (Figure 30).

Figure 31. Wanhua Chemical Group Co. LTD (600309.ss)—Daily

Figure 31 shows an example from the Shanghai stock exchange; a bearish symmetrical triangle pattern followed by a pullback movement is spotted in a daily chart of the Wanhua Chemical Group. The price target of the pattern was hit within the determined time target zone between September 3, 2008, and October 13, 2008.

Figure 32 shows another bearish symmetrical triangle price pattern, but without a pullback movement. The daily chart of Alphabet INC illustrates that the price hit the target within the determined time target.

Figure 32. Alphabet INC (GOOGL.O)—Daily

Bullish and bearish head and shoulders price patterns

Figure 33. Orascom Development (ORHD.CA)—Hourly

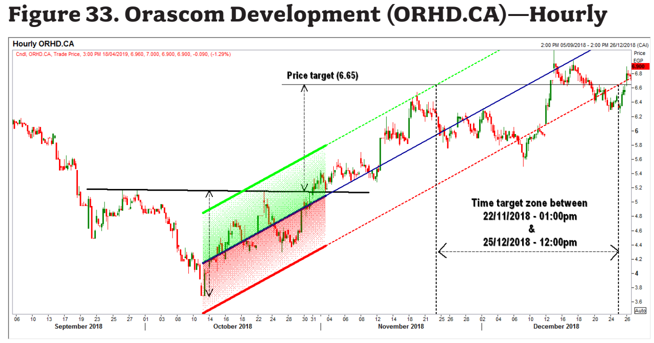
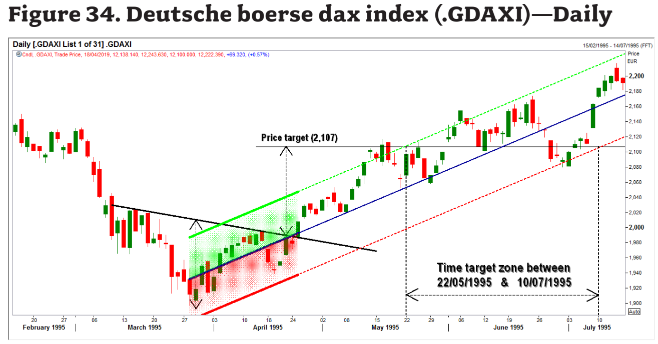


Figure 34. Deutsche boerse dax index (.GDAXI)—Daily



An hourly chart of Orascom Development Egypt shows a bullish head and shoulders price pattern followed by a pullback movement and its target that was hit within the determined time target zone between November 22, 2018 at 1:00 pm, and December 25, 2018 at noon (Figure 33).

Figure 34 shows another bullish head and shoulders price pattern but with no pullback movement. The daily chart of the main index of the Germain stock market illustrates that the price target of the completed pattern was achieved within the determined time target zone.

Figure 35. Egyptian Financial and Industrial SAE (EFIC.CA)—Weekly

Figure 36. EGX30 (.EGX30)—Daily

Two more examples of bearish head and shoulders price pattern from the Egyptian stock market appear in Figures 35 and 36. The weekly chart of the Egyptian Financial and Industrial stock shows an example of the pattern followed by a pullback movement while the daily chart of the main index shows another example without a pullback movement. In the two cases, the price targets were achieved within the determined time target zone.

Statistical Analysis of Time Target Zones of Price Targets of Classic Price Patterns

In a visual inspection of the daily data of the S&P 500 index, the Light crude oil and the EUR/USD pair from January 1, 2008, until December 31, 2018, disclosed 38 double top or bottom patterns, 21 triple top or bottom patterns, 27 rectangle patterns, 19 ascending triangle patterns, 23 descending triangle patterns, 28 symmetrical triangle patterns, and 49 head and shoulders patterns that achieved their price targets (Figure 37).

Figure 37. Frequency distribution of successful price patterns that appeared in the three instruments across the investigation period

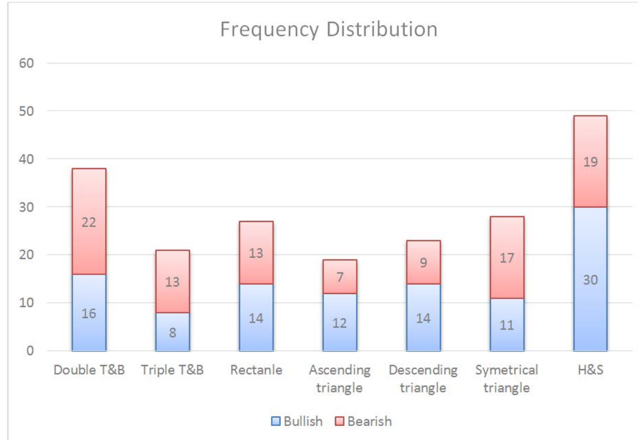


Figure 38 shows that 92% of double tops and bottoms patterns succeeded in achieving the price target of the pattern within the determined time target zone, while only 8% failed; 95% of triple tops and bottoms price patterns succeeded while only 5% failed; 100% of rectangle price patterns succeeded; 84% of ascending triangle price patterns succeeded while 16% failed; 91% of descending triangle price patterns succeeded while only 9% failed; 71% of symmetrical price patterns succeeded while only 29% failed; and finally, 84% of the H&S price patterns succeeded in achieving the price target within the determined time target zone while only 16% failed.

Figure 38. The success rate of achieving the price target within the determined time target zone for all patterns

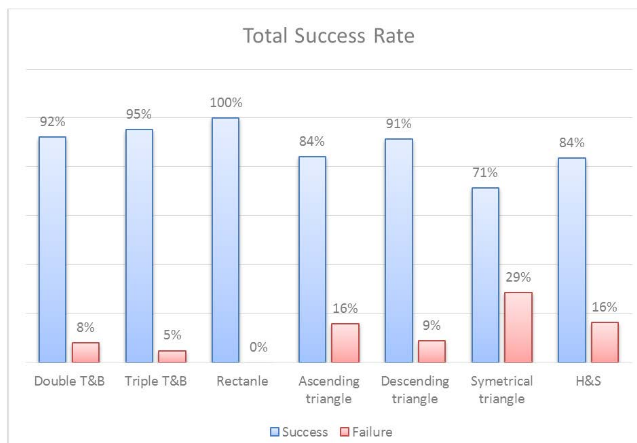


Figure 39 shows that most of the bullish patterns have succeeded in hitting their price target within the determined time target zone more than triple the failure times except for the bullish symmetrical triangle pattern, which recorded a moderate success rate.

Figure 39. The success rate of achieving the price target within the determined time target zone for bullish patterns

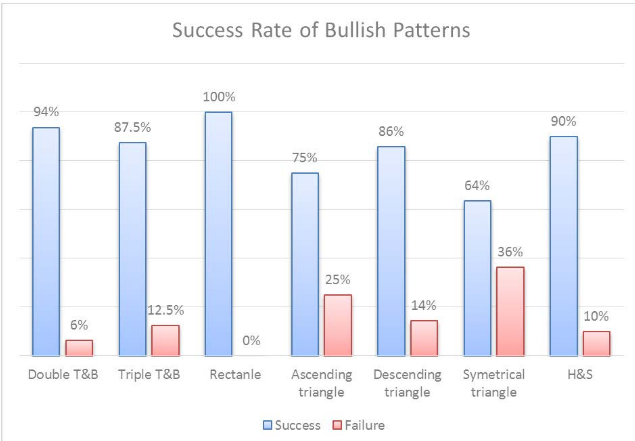
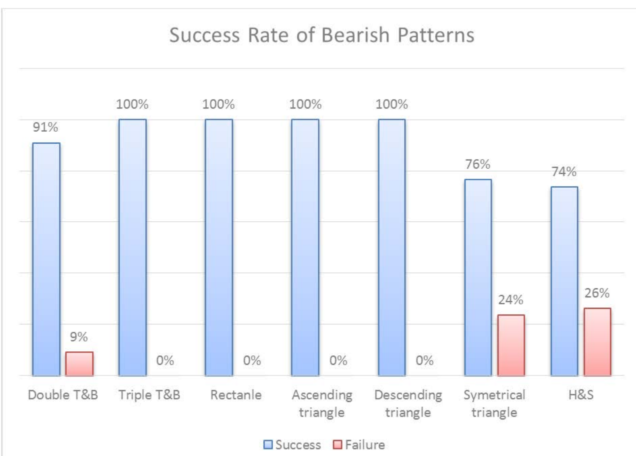


Figure 40. The success rate of achieving the price target within the determined time target zone for bearish patterns



On the other hand, Figure 40 reflects the superiority of the bearish patterns with four patterns recording the full mark and the rest recording sufficiently high success rates.

Figure 41 shows the number of patterns followed by a pullback movement before achieving the price target out of the total patterns that appeared.

Figure 41. Frequency distribution of successful price patterns that followed by pullback movements that appeared in the three instruments across the investigation period

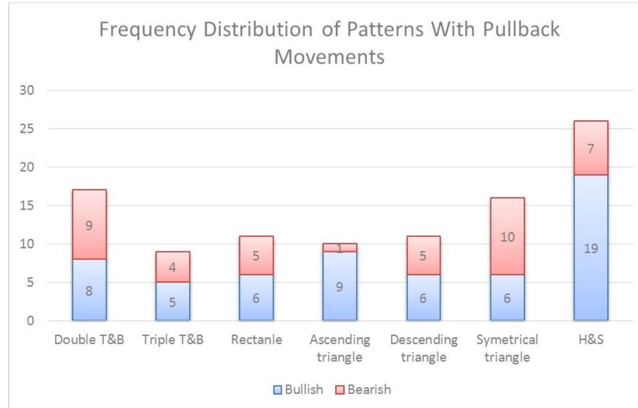


Figure 42. The success rate of achieving the price target within the determined time target zone for bullish patterns with pullback movements

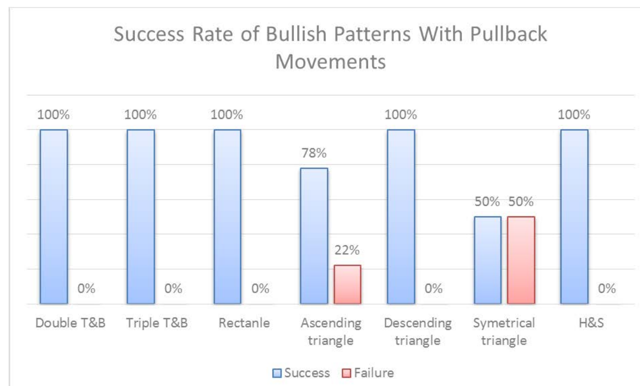


Figure 42 shows that again, except for the bullish symmetrical triangle patterns followed by pullback movements, which recorded a 1:1 success rate, five patterns recorded the full mark, and the rest recorded sufficiently high success rate.

Figure 43 shows superiorly high success rates for bearish patterns followed by pullback movements, including higher rates for the bearish symmetrical triangle and bearish ascending triangle patterns than the bullish ones.

Figure 43. The success rate of achieving the price target within the determined time target zone for bearish patterns with pullback movements

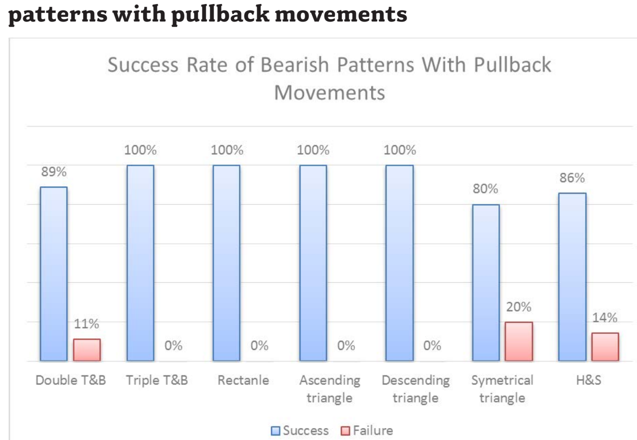


Figure 44. Frequency distribution of successful price patterns that weren't followed by pullback movements which appeared in the three instruments across the investigation period

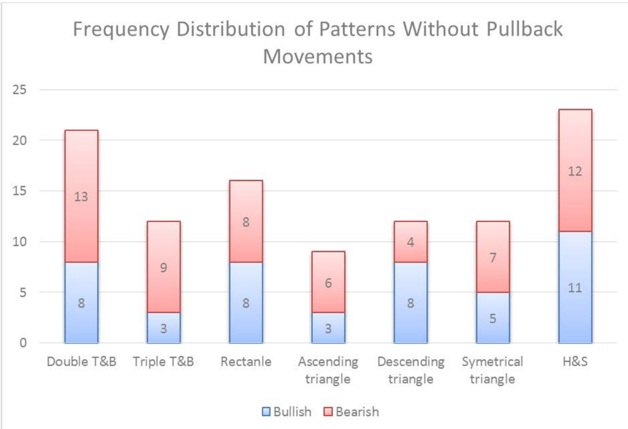
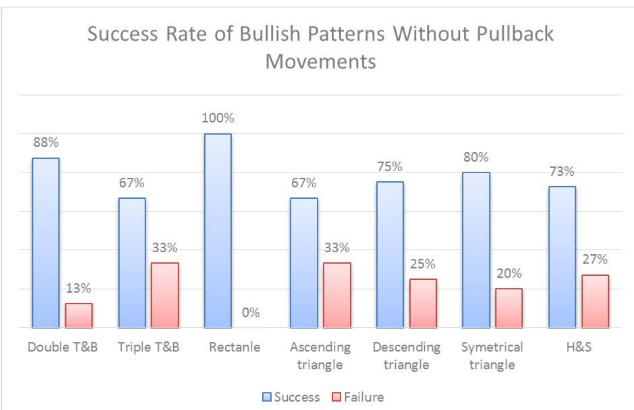


Figure 44 shows the number of successful patterns that achieved their price target directly after the breakout without pullback movements out of the total patterns that appeared.

Figure 45. The success rate of achieving the price target within the determined time target zone for bullish patterns without pullback movements



Figures 45 and 46 show that the bearish patterns that weren't followed by a pullback movement recorded higher success rates than the bullish ones except for the symmetrical triangle and the head and shoulders patterns.

Figure 46. The success rate of achieving the price target within the determined time target zone for bearish patterns without pullback movements

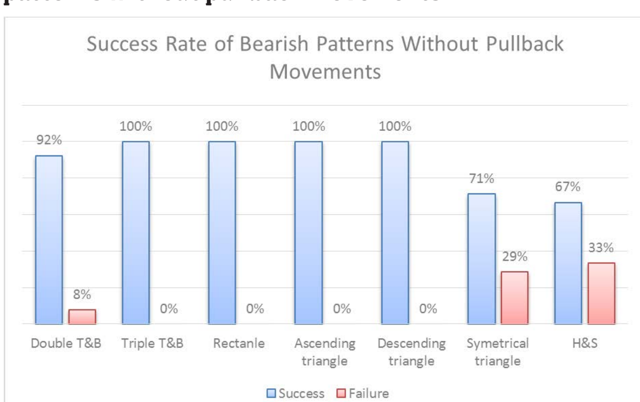
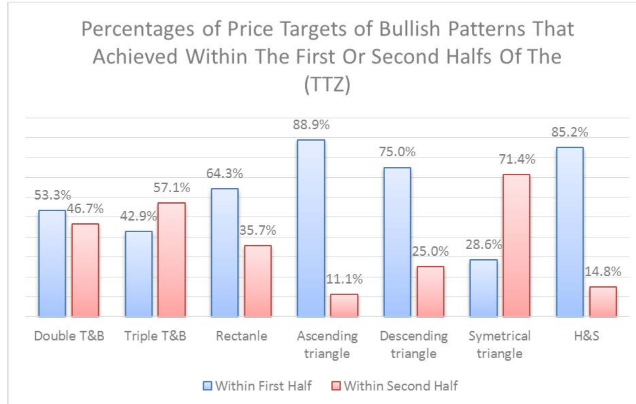
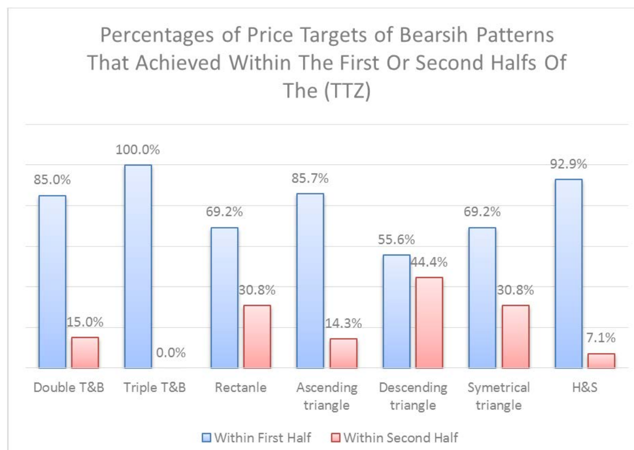


Figure 47. Percentages achieving the price target within the first or second half of the determined time target zone for bullish patterns



Figures 47 and 48 show that in general, price targets of the bearish patterns are achieved most often within the first half of their time target zones, despite the bullish ascending and descending triangle patterns proving better performance in that matter.

Figure 48. Percentages achieving the price target within the first or second half of the determined time target zone for bearish patterns



Summary

Identifying an expected return (or—as in technical analysis' terminology—a price target) is an advantage in the financial markets environment, however definitely, if it is accompanied by a time target to be achieved in, it will be superior.

This paper introduced an approach that tried to add more value to seven of the classic price patterns through the ability to identify time target zones for their traditional price targets by applying linear regression on the last price swing in the price pattern.

A variety of examples from various financial markets on multiple timeframes and throughout multiple decades were included in this paper as proof of the validity and applicability of the thesis throughout the age of the classic price patterns.

Finally, like any tool or approach, our approach also is not infallible, despite the result of the statistical analysis of the examined data reflecting satisfying overall success rates. Moreover, the bearish patterns seemed to have the upper hand, especially in achieving the targets within the first half of the determined time target zone.

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Notes

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Software and Data

Data and charts provided by Reuters.

Emerging Currencies as Equity Earthquake Indicator

By Ron Albert Marcelino Acoba, CFTe, CMT, MFTA

Ron Albert Marcelino Acoba, CFTe, CMT, MFTA

39 Guatemala Street, Loyola Grand Villa
Barangay Pansol
Quezon City, Metro Manila 1108
Philippines

+639175814766
ronacoba@gmail.com

Abstract

Investing in the equity markets traditionally entails institutional analysts and investors alike to primarily focus on corporate earnings and the health of the economy by looking at macro indicators such as GDP growth, inflation, an unemployment rate, among others, along with the price and volume actions of the general market and individual issues. Not much attention, however, is given to the impact of adverse movements in currencies in relation to equities. Unbeknownst to many retail investors, currency volatility is a major catalyst of hot money flight. The aim of this paper is to demonstrate that the movements in emerging currencies can be used as a seismograph to forecast short-run equity movements and as cues to actively defend against market aftershocks.

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Introduction

Seismograph

A seismograph or a seismometer, first invented in the 2nd century in China, is an instrument that measures and records the movements in the earth or "seismic waves" caused by an earthquake, volcanic activity, explosion, or other earth-moving phenomena. A seismograph produces a record of earth movements onto a screen or a paper printout. This is called a seismogram or, in terms of the financial markets, a price chart.

History is rich with notable earthquakes—from the deadliest ever recorded in Shaanxi, China, in 1556, to Kobe in Japan in 1995, to Aceh, Indonesia, in 2004, and to Haiti in 2010. In a similar fashion, the financial markets are likewise rich in notable currency events that placed a lot of economies and investors alike to their knees. This paper first looks at the history of different currency crises in the emerging markets and assesses their consequent impact on their respective equity market. We can then use the quantitative observations of the past to actively defend our portfolio from aftershocks in the equity markets should they occur later on.

Historical Anecdotal Precedents

Asian financial crisis

The epicenter of the Asian financial crisis that crumbled much of East Asia's economy was in Thailand. For most of the 1980s and 1990s, Thailand, along with South Korea, Singapore, Taiwan, and Hong Kong, was in a boom cycle. The group was actually termed as "Tiger economies" due to the high GDP growth that they were seeing in the period. Thailand's economy for its part at one point grew by a high of 11.2% in the 1990s. The high growth that the region, particularly Thailand, was seeing attracted a lot of foreign funds. Cheap interest rates of dollar denominated borrowings, false security by corporate borrowers due to the Thai government's encouragement or "guarantee," and a fixed exchange rate regime eventually led to over borrowing. There came a point where funds were being channeled to negative NPV ventures (Corsetti and others 1998).

An unprecedented amount of capital inflows, together with a drop in exports, widened the country's current account deficit (Aghevli 1999). What made matters worse was that a good portion of the capital inflows came in as short-term borrowings (Carson and Clark 2013). This situation eventually sparked an external attack by shorters on the Thai Baht (Dumlao 2017). It also did not help that the government burnt a good amount of their dollar reserves in their attempt to keep and protect the peg. The 25 Baht to $1 peg was shortly uncorked to 30 Baht to $1 on July 2, 1997. This event led to a series of currency devaluations that griped East Asia. In the first seven months after the central bank of Thailand unpegged their exchange rate, the Baht fell to a low of 56.75 against the USD. Similarly, the Korean Won fell to a low of 1,995 against 1 USD from only 888 at the end of June 1997. The Indonesian Rupiah suffered a far worse blow as it weakened to a low of 15,650 against 1 USD from only 2,431.50. The Malaysian Ringgit and the Philippine Peso likewise suffered more or less the same fate as their respective currencies melted to 4.88 from 2.52 and 46.80 from 26.38 against the greenback.

As investors dropped the Asian currency denominated assets like hot stone fresh from a spewing volcano, the Asian equity markets likewise faced a similar demise. The Thailand Stock Market (SET50) fell from a high of 535 in July 1997 to a low of 134 in the next 18 months. The Korea Stock Exchange Composite Index (KOSPI) fell from a high of 782 to a low of 277 in the same period. Indonesia's Jakarta Stock Price Index (JCI) fell from a high of 742 to a low of 255. Malaysia's Kuala Lumpur Composite Index (KLCI) declined to a low of 261 from a high of 1,085 while the Philippine Stock Exchange Index (PHISIX) slumped to a low of 1,075 from a high of 2,815 in the 18 months after July 1997.

Table 1. THBUSD versus SET 50 (July 1, 1997, to December 30, 1998)

	THBUSD	SET 50
1-month % change	-23.79%	28.85%
3-month % change	-31.98%	8.45%
6-month % change	-47.97%	-31.98%
12-month % change	-42.02%	-53.31%
18-month % change	-33.10%	-32.76%
drawdown	-56.90%	-64.73%

Table 2. KRWUSD versus KOSPI (October 17, 1997, to April 19, 1999)

	KRWUSD	KOSPI
1-month % change	-9.15%	-15.12%
3-month % change	-42.32%	-9.69%
6-month % change	-33.94%	-23.10%
12-month % change	-31.04%	-36.13%
18-month % change	-24.61%	30.93%
drawdown	-54.24%	-52.63%

Table 3. IDRUSD versus JCI (July 9, 1997, to January 11, 1999)

	IDRUSD	JCI
1-month % change	-6.96%	-9.72%
3-month % change	-27.59%	-26.72%
6-month % change	-72.19%	-51.99%
12-month % change	-84.15%	-36.48%
18-month % change	-69.40%	-39.97%
drawdown	-85.94%	-64.95%

Table 4. MYRUSD versus KLCI (July 10, 1997, to January 11, 1999)

	MYRUSD	KLCI
1-month % change	-9.57%	-10.55%
3-month % change	-19.90%	-17.30%
6-month % change	-46.36%	-52.65%
12-month % change	-41.84%	-57.50%
18-month % change	-34.50%	-40.66%
drawdown	-49.04%	-74.09%

Table 5. PHPUSD versus PHISIX (July 10, 1997, to January 11, 1999)

	PHPUSD	PHISIX
1-month % change	-7.79%	2.44%
3-month % change	-20.60%	-17.91%
6-month % change	-40.18%	-38.95%
12-month % change	-36.90%	-28.23%
18-month % change	-29.49%	-14.79%
drawdown	-43.38%	-57.18%

1Malaysia Development Berhad (1MDB) Scandal

The 1MDB scandal is an incident that placed a spotlight on Malaysia's corruption-laden government dealings. 1MDB was a government-run investment company with the mission to promote the country's long term development and foreign capital investments. Its interests were mainly centered on energy, tourism, real estate, and agriculture. In July 2015, then Prime Minister Najib Razak, who was the advisory board chairman, was accused of siphoning roughly $700 million from the company to his personal accounts (Wright and Clark 2015). The U.S. DOJ claimed that the in-crowd of the prime minister led by businessman Jho Low channeled money from 1MDB to various shell companies. Some of the funds were used to pay bribes and kickbacks to different politicians while the rest were allegedly embezzled for personal the use of Najib and Low (Wright 2015). Swiss authorities said that as much as $7 billion flowed from 1MDB and its units (Adam and others 2018). The news of embezzlement, corruption, money laundering, and betrayal of public trust, among others, by no less than the prime minister of Malaysia, cast an ash cloud on the country's economy and political leadership.

Prior to the 1MDB scandal, the Malaysian Ringgit was already reeling because of the 45% slide in the global prices of crude (WTIC) from its June 2014 high to the end of June 2015. Crude was Malaysia's number 1 export and a slip in price naturally meant lesser dollars flowing into the government's coffers (Y-Sing 2014). The scandal that came into light in July all the more gave foreign investors the reason to flee the country. This was then aggravated further when China devalued the Yuan in August 2015 in their attempt to shore up their exports (Farrer 2015). From July 1, 2015, the US dollar to Malaysian Ringgit exchange rate zoomed from 3.78 to a high 4.48 inside just 3 months. In the same time period, the Kuala Lumpur Composite Index fell from 1,706 to a low of 1,503.

Table 6. MYRUSD versus KLCI (July 1, 2015, to January 2, 2017)

	MYRUSD	KLCI
1-month % change	-2.78%	0.94%
3-month % change	-15.13%	-5.74%
6-month % change	-13.81%	-4.32%
12-month % change	-6.31%	-4.73%
18-month % change	-16.50%	-4.99%
drawdown	-16.50%	-12.98%

Indian Rupee Slide

The US dollar to Indian Rupee exchange rate of the USDINR pair had surged 16.68% to a high of 74.48 in October 2018 from just 63.83 at the beginning of the year. The steep slide of the Rupee can be attributed to a confluence of global economic developments. Firstly, the U.S. Federal Reserve embarked on a more aggressive monetary policy. It continued to raise its benchmark interest from 1.5% to 1.75% in March 2018 after already raising it three times in the prior year. Robust employment figures and GDP growth led the Fed to hike its rates anew to 2% in June while signaling that it would do so for a total of four times in all of 2018. The Fed's actions sparked a massive capital outflow from emerging markets as U.S. yields became more attractive. Consequently, the Fed's policy also lessened the availability of the USD in the global system, which further pushed its value and likewise placed downward pressure on emerging currencies like the Rupee (Sengupta 2018).

Another event that contributed to the Rupee's slide was the 28.3% surge in the global prices of crude as measured in the West Texas Intermediate Crude (WTIC). WTIC jumped from just $60.07 per barrel at the start of 2018 to a high of $77.07 per barrel in October. A decrease in daily production by OPEC and Russia plus the United States's sanctions on Iran curbed the supply of crude, which therefore translated into an increase in its price. With India importing about 70% of its crude demand, the increase in its price only worsened India's current account deficit. In addition, the "trade war" between the United States and China plus the latter's currency devaluation further triggered more emerging market-to-develop markets flows (Singh 2019). In the period where the USDINR rose by 16.68% to 74.48 in October 2018 from 63.83 at the start of January, India's BSE SENSEX still managed to edge higher by 2.07% to 34,760. This came despite a strong GDP growth of 7.1% to 8.2% in its most recent quarters. It would have fared much higher if only the Rupee had been stable.

Table 7. INRUSD versus BSE SENSEX (January 1, 2018, to January 1, 2019)

	INRUSD	BSE SENSEX
1-month % change	0.46%	5.60%
3-month % change	-1.96%	-3.20%
6-month % change	-6.75%	4.01%
12-month % change	-8.24%	5.91%
18-month % change	NA	NA
drawdown	-14.30%	-4.62%

Turkey Currency Crisis

Turkey's currency crisis bore as a result of the country's appetite for foreign-denominated debt. In the recent years, Turkey's economy has been growing at a very robust clip, even rising by a high of 7.5% for the entire 2017. Much of its growth, however, was fueled by high levels of government expenditure funded by foreign-denominated debt (Lee 2018). As of the end of 2017, Turkey's gross external debt, which includes public and private loans, reached $453.20 billion. With roughly 40% of the said amount, or ~$180 billion, set to mature in 2018, plus the fact that the country only has a gross currency reserve of $85 billion, investors started to become wary of Turkey's capability to service its maturing debt (Holland 2018). To add fuel to the fire, the USD had likewise started to strengthen on the back of the U.S. Federal Reserve's tightening policies. Additionally, the Central Bank of the Republic of Turkey's decision to keep its interest rates steady at 8% even at the face of a double-digit inflation rate added more pressure on the currency. It was actually Turkish President Recep Tayyip Erdogan who prevented the central bank from increasing their interest rates. He most famously, or infamously, rather stated that "interest rates are the mother and father of all evil" (Baccardax 2018). The president of Turkey's interference with the central bank ran contrary to the notion that central banks should be left independent. Furthermore, the economic sanction imposed by the United States to Turkey by doubling its tariffs on Turkish steel and aluminum placed more pressure on the country's already ballooning current account deficit (Harper 2018).

As expected, investors let go of Turkish financial assets following the steep slide in the Turkish Lira. The above factors resulted to a sharp depreciation of the Lira against the U.S. dollar, with the USDTRY exchange rising to a high of 7.083 in August 2018 from only 3.791 at the end of December 2017. This of course cascaded into a 26.6% drop in the Borsa Istanbul 100 Index.

Table 8. TRYUSD versus BIST 100 Index (January 1, 2018, to January 1, 2019)

	TRYUSD	BIST 100 Index
1-month % change	0.92%	3.64%
3-month % change	-4.18%	-0.35%
6-month % change	-17.38%	-16.31%
12-month % change	-28.34%	-20.86%
18-month % change	NA	NA
drawdown	-47.65%	-26.60%

2015 Ghost Month: The Yuan Devaluation

The global financial markets, particularly the Asian emerging markets, were visited early by the "hungry ghosts" as China enacted a series of unexpected devaluations of its currency, the Yuan, against the U.S. dollar. On August 11, 2015, exactly three days before the beginning of the Chinese Ghost Month, the Chinese central bank weakened the Renminbi by 1.86% to 6.2298 per U.S. dollar (Mo 2015). A day later, a huge tidal wave of selling continued to grip the financial markets as the People's Bank of China pushed their currency down by another 1.62% against the greenback (Riley 2015). It did not actually stop there, as the bank, for a third day in a row, softened it further to 6.3975 per U.S. dollar (Inman 2015). The central bank's actions came following an 8.3% slide in exports in July from a year ago (Vaswani 2015). Many believe that the bank's moves were intended to shore up the country's international trade. According to the PBOC, however, the "adjustment in the fixing rate formation mechanism was aimed at correcting the disparity between the fixing rate and the spot rate of the Chinese Yuan against the U.S. dollar" since the Yuan, being pegged with the USD, had been steadily rising in value along with the greenback on the back of the planned monetary tightening in the United States. Additionally, PBOC's actions were also meant as a bid to join the IMF's Special Drawing Rights basket (Chin 2015).

Nonetheless, shockwaves were sent not just in the currency markets but likewise in the equities and commodities spaces following the surprise move from the Chinese. With the USDCNY exchange rate rising from 6.2093 in August 10, 2015, to a high of 6.4485 in the next three days, capital outflows from China and even from the rest of Asia accelerated as a consequence. In the following two weeks, the Shanghai Composite Index fell by 27.44% from 3,928 on August 10 to a low of 2,850.

Table 9. CNYUSD versus SSE Composite (August 10, 2015, to February 10, 2017)

	CNYUSD	SSEC
1-month % change	-2.63%	-18.60%
3-month % change	-2.39%	-7.33%
6-month % change	-5.54%	-30.09%
12-month % change	-6.45%	-23.16%
18-month % change	-9.72%	-18.63%
drawdown	-10.83%	-32.84%

Literature

John Murphy, CMT, a living legend in the field of technical analysis, noted the concept of intermarket analysis in his book *Trading with Intermarket Analysis* (2012). Here, he said that intermarket analysis involves the examination of different asset classes, bonds, stocks, commodities, and currencies. The premise of intermarket analysis is that these asset classes are related. This means that what happens in one market also has an impact on the other asset classes. In his book *Intermarket Analysis: Profiting from Global Market Relationships,* he noted that "a falling currency usually gives a boost to commodity prices quoted in that currency. This boost in commodity prices reawakens inflation fears and puts pressure on central bankers to raise interest rates, which has a negative impact on the stock market" (Murphy 2004). He actually first introduced the concept of intermarket analysis in his book *Intermarket Analysis: Trading Strategies for the Global Stock, Bond, Commodity, and Currency Markets*. Here, he mentioned that a "rising dollar will eventually push inflation and interest rates lower, which is bullish for (US) stocks and a falling dollar will eventually push (US) stock prices lower because of the rise in inflation and interest rates. However, it is an oversimplification that a rising dollar is always bullish for (US) stocks and a falling dollar is always bearish for (US) equities" (Murphy 1991). It is the aim of this paper to see whether this premise also applies in the emerging market economies, specifically in East Asia. Of course, other dimensions, like the Asian economy's exposure to dollar denominated debt, exposure to hot capital flows, and the account of imports and exports in relation to their GDP, also play important roles.

In a study done by Clive Granger, Bwo-nung Huang, and Chin Wei Yang (1998), evidence was found of a bivariate causality between stock prices and exchange rates. Using the Asian flu data of the 1990s, they found that in at least South Korea and Thailand, exchange rates lead stock prices with a positive correlation and that the "inclusion of exchange rate variations is found to have improved the predictable portion of stock price changes of the eight Asian economies." They also found, though, that at times, stock prices lead the changes in the exchange rates. They further concluded that with the opening of Asian economies to trade and global financing, capital movement into and out of the Asian economies can be both beneficial and detrimental, as in the case of the Asian financial crisis, where a lot of capital flew out of the region. Abdul Qayyum and A.R. Kemal (2006) also found that volatility in the exchange rate has a spill over in the Pakistani stock market and vice versa. In the same way, Dr. Alok Kumar Mishra, A.K. Swain, and D.K. Malhotra (2007) found bi-directional volatility spillovers between the Indian equity market and its exchange rate. Meanwhile, Usman Umer, Guven Sevil, and Serap Kamisli (2015) determined that the "comovements between exchange rates and stock prices become stronger during the crises time, and the direction of causality originates from stock prices to exchange rates during the tranquil period; and from exchange rates to stock prices during crisis."

Additionally, Valentina Bruno and Hyun Song Shin (2018) found that "non-financial firms that exploit favorable global financing conditions to issue bonds and build cash balances are also those whose share price is most vulnerable to local currency depreciation." They further found that while currency depreciation would be favorable for exporting firms, the impact of the financial burden from their foreign-denominated debt outweighs their supposed competitiveness. According to Rudiger Dornbusch and Stanley Fischer (1980), changes in the exchange rates impact the competitiveness of firms, as it affect the firms' cost of capital and earnings which in turn get reflected on its share price. They added that on a macro level, the impact of exchange rate movements on the equity market would likewise be hinged on the "degree of openness of the economy and the degree of trade imbalance." Christopher Ma and G. Wenchi Kao (1990) found that on a macro level, an appreciation of the domestic currency negatively affects the domestic stock market of an export-oriented economy, while a depreciation of the local currency positively affects the equity market of an import-oriented one.

Methodology

Association Analysis

For association analysis, Pearson Correlation Analysis was used to find the correlation of 10-year historical prices of emerging market indices against their respective currency (historical data of sample equity indices, their respective currency exchange, and the US Dollar Index were sourced from Investing.com and TradingEconomics.com). This type of correlation analysis is used to determine the degree of linear relationship between two quantitative variables that are assumed normally distributed. Essentially, three questions will be answered by the corresponding Pearson's coefficient: (1) Is there a linear relationship? (2) How strong is it? (3) What is the direction of the linear relationship?

Sample Pearson correlation coefficient is computed as

$$r = \frac{s_{XY}}{s_X s_Y}$$

where the numerator estimates the covariance between the two variables (say X and Y), and the denominator is the product between the two sample standard deviations.

The sample Pearson correlation coefficient, r, takes on values from -1 to +1. A value very near -1 indicates an almost perfect inverse (or indirect) linear relationship between two variables, while a correlation coefficient very near +1 indicates almost perfect direct linear relationship. On the other hand, a value very near zero implies absence of linear relationship, but this does not mean absence of another form of relationship (other than linear).

As a rule of thumb, the qualitative interpretation for the correlation coefficient is given below. If the coefficient is negative, the variables are moving at opposite directions (as one decreases, the other one increases or vice versa) but if the coefficient is positive, the variables are moving in the same direction (as one decreases [or increases], the other one also decreases [or increases]).

0:	No association
0.01 – 0.20:	Very weak association
0.21 – 0.40:	Weak association
0.41 – 0.60:	Moderate association
0.61 – 0.80:	Strong association
0.81 – 0.99:	Very strong association
1:	Perfect association

The association tables note the year group used in the analysis. Year group 2017–2018 used all observations within these years, as is the case for year group 2011–2018. Take note that for Thailand and India, only up until 2011 is available, so the year groups for these countries are the recent two years and the recent eight years. For the other countries, year 2009 is available, so the year groups are 2017–2018 (recent two years) and 2009–2018 (recent 10 years).

For each year group, the stock market of the of a sample Asian emerging market represented by its equity index is correlated to the respective local currency exchange rate and USD Index (reciprocal) resulting to four coefficients stated under the 3rd column. Qualitative interpretation for each coefficient is also given under the 4th column. The last column lists the p-value associated with the estimated correlation coefficient. p-values help us decide for the statistical significance of the estimate. From this point onward, we reject the null hypothesis (Ho) of the appropriate test if the p-value is small (e.g., less than 0.10). Otherwise, Ho is accepted. Rejecting the Ho means that the conclusion will support the alternative hypothesis (Ha). For Pearson Correlation Analysis, the set of hypotheses are:

Ho: The two variables are not associated.

Ha: The two variables are associated.

Significant results (Ho is rejected) are noted by two asterisks (**) printed beside the p-value while nonsignificant results (Ho is accepted) are noted by (^{ns}).

Dependence of Stock Market: Selection of Lag Order

Lag refers to the interval between present and past values and is vital when dealing with time series data since past values are usually correlated to present values. Before modelling, it is important to know which lag has the highest contribution to the behavior of the time series data. The criteria that we will use to determine the number of lags in the model are final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and Hannan-Quinn information criterion (HQIC). Smaller values for these criteria mean better modelling capability. If the lag order is suggested by most of these criteria, that lag order is used. If exactly two of these criteria suggested two different lag orders, the lowest order is chosen due to issue of parsimony and ease of interpretation. Parsimony refers to the ability of the model to explain the dependent variable given minimal number of predictors.

Dependence of Stock Market: Association Tests

For time-series modeling to be applicable, the time-series must be stationary. Through time, the behavior of the variable must not show any trend (increasing or decreasing) or fluctuations that resemble a pattern. Such time-series must be detrended or must be transformed into a stationary process. Augmented Dickey-Fuller Tests can check whether the time-series data is stationary or not by hypothesizing about the unit-root. If a variable has a unit-root, then the variable follows a random walk or a behavior with an unpredictable pattern.

Ho: The time-series data has a unit-root. (Not stationary)

Ha: The time-series data is a stationary process.

In here, we tested for the stationarity of the levels (actual value) and the first-differences (current minus previous). First-difference is a useful concept in time-series modelling since it shows the change between successive values.

Dependence of Stock Market: Regression Models of Stock Market

Four linear regression models for change in the equity index (dependent variable) are used. Two models used only the individual exchange rate as predictor at varying year groups and another two models used both the exchange rate and the USD Index (reciprocal) as predictors, also at varying year groups.

Each table under a certain year group lists the coefficients (impact or effect) of the predictor to the change in the equity index. Accompanying each coefficient is its p-value. Stated in the last row is the coefficient of determinations R-squared which tells us the percentage of variation in the dependent variable that can be explained by the predictors. Higher R-squared means better predictive ability of the model. If the coefficient and p-value are blank, it means that the corresponding predictor is not included in that model. Take note that predictors are dictated by the lag order selected in previous analyses.

For example, the THB/USD exchange rate in 2017–2018 has lag order 1, so the lag of the first-differenced THB/USD exchange rate denoted by L1D is included in the model below. **D** refers to the first-difference while **L** refers to the lag, and the number attached to it is the order.

MSCI Emerging Market Index Versus MSCI EM Currency Index Test

On top of the establishment of correlation and causation between samples of individual emerging market currencies to their respective equity markets (Baht vs. SET, Rupee vs. BSE SENSEX, Lira vs. Borsa Istanbul, Ringgit vs. Bursa Malaysia, Rupiah vs. JCI), and domestic currency along with the reciprocal of the US Dollar Index against the respective equity market for the periods 2017–2018 and 2009–2018, the paper will also look for the correlation and causation between the MSCI Emerging Markets Currency Index and the MSCI Emerging Markets Index.

It is likewise important to subject the MSCI Emerging Markets Index against its currency index because of the widespread use of both indices as a benchmark of global funds. As per the MSCI.com website, the MSCI Emerging Market Index was launched in 1988. Back then, it only consisted of 10 countries representing less than 1% of global market capitalization. Since then, the index has grown to include 24 economies, namely Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, Qatar, South Africa, Taiwan, Thailand, Turkey, and the UAE. As of September 2018, China has the heaviest weight, accounting for 30.99% of the index. South Korea and Taiwan account for 14.88% and 12.29%, respectively, in the index. The index captures both large and mid-cap representations across the said countries and also covers approximately 85% of the free-float adjusted market capitalization in each country.

Meanwhile, the MSCI EM Currency Index includes currencies from 25 emerging market countries. Currencies from Asian emerging markets account for a little over half of the weight of the index at 50.2%. On the other end, currencies from emerging Europe and the Middle East (EMEA) and emerging Latin America comprise about a quarter each of the weight of the index. For emerging Asia, the weights of the Chinese Yuan and the Korean Won are 14.5% and 13%, respectively. Additionally, the Brazilian Real has a 16.9% weight under the emerging Latin America.

Theoretically, strength in the EM Currency Index should translate to a consequent rise in the equity space as measured in the MSCI Emerging Market Index and vice versa. Using the daily data from January 12, 2015, to April 1, 2019, we shall establish a correlation and causation via regression analysis between the two indices. Additionally, we will also look to quantify the resulting decline measured in the following month, two and three months in the equity index for every 2% break in the currency index. A "break" in the currency index is defined as a fall below an established swing low in its daily bar chart. The same will also be measured for a 2% decline from an established swing high or peak. These technical breaks in the currency index shall be deemed as "signals" for a possible drop in the emerging equity index.

Results

Results for Thailand

Association of Bangkok SET50 Index to THB/USD Exchange Rate and USD Index (reciprocal)

Table 10. Correlation coefficients and P-values of SET50 to THBUSD and US Dollar Index

Year Group	Association of Stock Market to:	Pearson's Correlation Coefficient	Interpretation	p-value
2017–2018	THB/USD Exchange Rate	0.1393	very weak & direct	0.002 **
	USD Index (reciprocal)	0.0541	very weak & direct	0.232 ns
2011–2018	THB/USD Exchange Rate	0.2400	weak & direct	<.001 **
	USD Index (reciprocal)	0.0322	very weak & direct	0.161 ns

The Bangkok SET50 Index had a very weak (r = 0.1393) direct linear association to THB/USD Exchange rate for the years 2017 to 2018 but shared stronger (r = 0.2400) direct linear association for the past eight years. Both were found to be statistically significant. On the other hand, its association to the USD Index (reciprocal), aside from being very weak, was also not significant. This implies that the Thailand stock market does not share linear association with the reciprocal of the USD Index. All associations were positive or direct, which means that when THB/USD exchange rate or USD index (reciprocal) increases (or decreases), the Bangkok SET50 Index also increases (or decreases).

Dependence of Bangkok SET50 Index: Selection of Lag Order

Table 11. Selected Lag Orders and LR Test P-value for SET50 to THBUSD and US Dollar Index

Year Group	Variable	Selected Lag Order	Suggested by:	LR Test p-value
2017–2018	Bangkok SET50 Index	1	all four	<.001 **
	THB/USD Exchange Rate	1	all four	<.001 **
	USD Index (reciprocal)	1	HQIC, SBIC	<.001 **
2011–2018	Bangkok SET50 Index	1	HQIC, SBIC	<.001 **
	THB/USD Exchange Rate	1	HQIC, SBIC	<.001 **
	USD Index (reciprocal)	2	FPE, AIC, HQIC	0.035 **

For the most recent two years, all variables are somehow dictated by the most recent previous value (lag of 1). The behavior of the Bangkok SET50 Index and THB/USD exchange rate is consistent even for the most recent eight years. However, the USD Index (reciprocal) is shown to be affected generally by the two previous values.

Note that these lags will be considered in the succeeding regression models.

Dependence of Bangkok SET50 Index: Stationary Tests

Table 12. Results of Dickey-Fuller Test for Bangkok SET50 Index to THBUSD and USD Index

Year Group	Variable	Dickey-Fuller Test p-value: At the level	Dickey-Fuller Test p-value: First-Difference	Remark
2017–2018	Bangkok SET50 Index	0.609 ns	<.001 **	First-differenced data is stationary.
	THB/USD Exchange Rate	0.972 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.881 ns	<.001 **	First-differenced data is stationary.
2011–2018	Bangkok SET50 Index	0.854 ns	<.001 **	First-differenced data is stationary.
	THB/USD Exchange Rate	0.816 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.883 ns	<.001 **	First-differenced data is stationary.

For all variables in either year groups, first-differences follow a stationary process. Since first-differences follow a stationary process, then the models for all countries will predict the change in the equity index and not the actual observed stock market. All interpretations should focus in the change in the equity index. However, take note that even if interpretations are directed to "change" in the equity index, mathematical characteristics of time series model can extend the interpretation at the levels (actual or non-differenced values). In other words, since all variables across different timeframes that were tested showed that their respective time series is a stationary process, this essentially means that the change in the Bangkok SET50 Index is somewhat predictable by the movements in the THB/USD exchange rate and the USD Index (reciprocal) and is not due to "random walk."

Dependence of Bangkok SET50: Regression Models of Bangkok SET50

Table 13. Regression results for Bangkok SET50 Index to THBUSD

	2017–2018		2011–2018	
Predictor	**Coefficient**	**p-value**	**Coefficient**	**p-value**
(L1D). Bangkok SET50 Index	-0.0003	0.996 ns	0.002	0.949 ns
(D).THB/USD Exchange Rate	16455.6	0.010 **	32884.91	<.001 **
(L1D).THB/USD Exchange Rate	9694.75	0.102 ns	1671.32	0.626 ns
R-squared	2.59%		5.78%	

Clearly, the THB/USD exchange rates are significantly positively associated to the Bangkok SET50 Index (positive coefficients) which implied that an increase in THB/USD exchange rates also increases the Bangkok SET50 Index. For 2017–2018, one unit increase in the previous (lag 1) change (difference) in the Bangkok SET50 Index caused a decrease (since it is negative) of 0.0003 to the current change in the Bangkok SET50 Index. Its effect is different for the recent eight years for the previous change in the Bangkok SET50 Index caused an increase of 0.002 to the current change. However, these estimated effects were found to be not statistically significant. Another non-significant predictor in the model is the previous change in THB/USD exchange rate. For both year groups, its effect is positive.

Significant effect was determined in the current change in the THB/USD exchange rate. A unit increase in the current change in the THB/USD exchange rate caused an increase of 16455.6 to the current change in the Bangkok SET50 Index in 2017–2018 and a higher increase of 32884.91 in 2011–2018. This can provide evidence that the Bangkok SET50 Index has linear dependence to THB/USD exchange rate.

Only around 2.59% of changes in the Bangkok SET50 Index can be explained by the three predictors during 2017–2018. Extending it to the most recent eight years, the predictors can explain 5.78% of variations in the Bangkok SET50 Index.

Table 14. Regression results for Bangkok SET50 Index to THBUSD and USD Index

	2017–2018		2011–2018	
Predictor	**Coefficient**	**p-value**	**Coefficient**	**p-value**
(L1D). Bangkok SET50 Index	0.00007	0.999 ns	0.002	0.934 ns
(D). THB/USD Exchange Rate	17433.39	0.013 **	37893.83	<.001 **
(L1D). THB/USD Exchange Rate	9289.26	0.153 ns	4721.59	0.226 ns
(D). USD Index (reciprocal)	-4478.54	0.702 ns	-21724.50	0.004 **
(L1D). USD Index (reciprocal)	1956.53	0.879 ns	-11770.09	0.058 **
(L2D). USD Index (reciprocal)	-	-	-2001.86	0.727 ns
R-squared	2.62%		6.58%	

Incorporating the USD Index (reciprocal) into the model switched the coefficient of previous change in the Bangkok SET50 Index from negative to positive. With a small effect, the test suggested that changes in the Bangkok SET50 Index are not significantly dependent to previous changes. With or without the USD Index (reciprocal), the THB/USD exchange rate still has significant direct effect to the Bangkok SET50 Index, especially the current (D) change in the THB/USD exchange rate.

The models above suggest that the USD Index (reciprocal) appears to have long-term effect to Thailand stock market. The USD Index (reciprocal) is not significant in the 2017–2018 year group but is significant in the 2011√2018 year group up to the first lag difference (L1D). The model of the longer year group also suggests that the USD Index (reciprocal) has indirect effect to the Bangkok SET50 Index, as seen in its negative coefficients. Specifically, an increase in the difference between successive USD Index (reciprocal) values causes a decrease of about 21724.50 units in the change in the Bangkok SET50 Index.

Results for Indonesia

Association of the Jakarta Stock Exchange Composite Index to IDR/USD Exchange Rate and USD Index (reciprocal)

Table 15. Correlation coefficients and P-values of Jakarta Stock Exchange to IDRUSD and US Dollar Index

Year Group	Association of Stock Market to:	Pearson's Correlation Coefficient	Interpretation	p-value
2017–2018	IDR/USD Exchange Rate	0.3312	weak & direct	<.001 **
	USD Index (reciprocal)	0.1060	very weak & direct	0.020 **
2009–2018	IDR/USD Exchange Rate	0.3491	weak & direct	<.001 **
	USD Index (reciprocal)	0.0321	very weak & direct	0.114 ns

The Jakarta Stock Exchange Composite Index (JSX) had a weak (r = 0.3312) direct linear association to IDR/USD Exchange rate for the years 2017 to 2018 but shared stronger (r = 0.3491) direct linear association for the past 10 years. Both were found to be statistically significant. Its association to USD Index (reciprocal), on the other hand, is very weak but direct and significant for 2017–2018. This implies that the Jakarta Stock Exchange Composite Index does share linear association with the reciprocal of the USD Index (reciprocal) in the short run. All associations were positive or direct, which means that when IDR/USD exchange rate or USD index (reciprocal) increases (or decreases), the Jakarta Stock Exchange Composite Index also increases (or decreases).

Dependence of Jakarta Stock Exchange Composite Index: Selection of Lag Order

Table 16. Selected lag orders and LR Test p-value for Jakarta Stock Exchange to IDRUSD and US Dollar Index

Year Group	Variable	Selected Lag Order	Suggested by:	LR Test p-value
2017–2018	Jakarta Stock Exchange Composite Index	1	*all four*	<.001 **
	IDR/USD Exchange Rate	2	*all four*	0.002 **
	USD Index (reciprocal)	1	*all four*	<.001 **
2009–2018	Jakarta Stock Exchange Composite Index	4	*all four*	<.001 **
	IDR/USD Exchange Rate	1	HQIC, SBIC	<.001 **
	USD Index (reciprocal)	1	*all four*	<.001 **

For the most recent two years, the Jakarta Stock Exchange Composite Index and the USD Index (reciprocal) are somehow dictated by the most recent previous value (lag of 1), while the IDR/USD exchange rate is shown to be affected by the two previous values. For the last eight years, both the IDR/UDS and the USD Index (reciprocal) are dictated by the most recent previous value, while the Jakarta Stock Exchange Composite Index is shown to be affected generally by the four previous values.

Dependence of Jakarta Stock Exchange Composite Index: Stationary Tests

Table 17. Results of Dickey-Fuller Test for Jakarta Stock Exchange to IDRUSD and USD Index

Year Group	Variable	Dickey-Fuller Test p-value: At the level	Dickey-Fuller Test p-value: First-Difference	Remark
2017–2018	Jakarta Stock Exchange Composite Index	0.667 ns	<.001 **	First-differenced data is stationary.
	IDR/USD Exchange Rate	0.709 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.926 ns	<.001 **	First-differenced data is stationary.
2009–2018	Jakarta Stock Exchange Composite Index	0.961 ns	<.001 **	First-differenced data is stationary.
	IDR/USD Exchange Rate	0.616 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.484 ns	<.001 **	First-differenced data is stationary.

All variables across different timeframes that were tested showed that their respective time series is a stationary process. This essentially means that the change in the Jakarta Stock Exchange Composite Index is somewhat predictable by the movements in the IDR/USD exchange rate and the USD Index (reciprocal) and is not due to "random walk."

Dependence of Jakarta Stock Exchange: Regression Models of Jakarta Stock Exchange

Table 18. Regression result for Indonesia (IDRUSD versus JSX)

	2017–2018		2009–2018	
Predictor	**Coefficient**	**p-value**	**Coefficient**	**p-value**
(L1D). Jakarta Composite Index	-0.03	0.615 ^{ns}	0.01	0.747 ^{ns}
(L2D). Jakarta Composite Index	-	-	-0.02	0.508 ^{ns}
(L3D). Jakarta Composite Index	-	-	-0.10	<.001 **
(L4D). Jakarta Composite Index	-	-	-0.04	0.072 **
(D). IDR/USD Exchange Rate	7.96 x 10^7	<.001 **	4.39 x 10^7	<.001 **
(L1D). IDR/USD Exchange Rate	-6570148.00	0.634 ^{ns}	3724836	0.212 ^{ns}
(L2D). IDR/USD Exchange Rate	1.81 x 10^7	0.111 ^{ns}		-
R-squared	11.71%		13.52%	

Significant effect was determined in the current change in the IDR/USD exchange rate. A unit increase in the current change in the IDR/USD exchange rate caused an increase of 7.96x107 to the current change in the Jakarta Stock Exchange Composite Index in 2017–2018 and an increase of 4.39 x 107 in 2009–2018. This can provide evidence that the Jakarta Stock Exchange Composite Index has linear dependence to the IDR/USD exchange rate.

Only around 11.71% of changes in the Jakarta Stock Exchange Composite Index can be explained by the three predictors during 2017–2018. Extending it to the most recent 10 years, the predictors can explain 13.52% of variations in the Jakarta Stock Exchange Composite Index.

Table 19. Regression result for Indonesia (IDRUSD and USD Index reciprocal versus JSX)

	2017–2018		2009–2018	
Predictor	**Coefficient**	**p-value**	**Coefficient**	**p-value**
(L1D). Jakarta Composite Index	-0.04	0.515 ^{ns}	0.01	0.732 ^{ns}
(L2D). Jakarta Composite Index	-	-	-0.02	0.500 ^{ns}
(L3D). Jakarta Composite Index			-0.10	<.001 **
(L4D). Jakarta Composite Index			-0.04	0.074 **
(D). IDR/USD Exchange Rate	7.83 x 10^7	<.001 **	4.40 x 10^7	<.001 **
(L1D). IDR/USD Exchange Rate	-1.41 x 10^7	0.307 ^{ns}	3857481.00	0.214 ^{ns}
(L2D). IDR/USD Exchange Rate	1.53 x 10^7	0.199 ^{ns}	-	-
(D). USD Index (reciprocal)	95492.15	0.108 ^{ns}	-5646.01	0.762 ^{ns}
(L1D). USD Index (reciprocal)	79895.24	0.174 ^{ns}	3053.63	0.831 ^{ns}
R-squared	12.62%		13.52%	

Incorporating the USD Index into the model showed that significant effect remained to be determined in the current change in the IDR/USD exchange rate. A unit increase in current change in the IDR/USD exchange rate caused an increase of 7.83 x 107 to current change in the Jakarta Stock Exchange Composite Index in 2017–2018 and an increase of 4.40 x 107 in 2009–2018. This can likewise provide evidence that the Jakarta Stock Exchange Composite Index has linear dependence to the IDR/USD exchange rate.

Only around 12.62% of changes in the Jakarta Stock Exchange Composite Index can be explained by the above predictors during 2017–2018. Extending it to the most recent 10 years, the predictors can explain 13.52% of variations in the Jakarta Stock Exchange Composite Index.

Results for Malaysia

Association of Bursa Malaysia KLCI Index to MYR/USD Exchange Rate and USD Index (reciprocal)

Table 20. Correlation coefficients and p-values for Malaysia

Year Group	Association of Stock Market to:	Pearson's Correlation Coefficient	Interpretation	p-value
2017–2018	MYR/USD Exchange Rate	0.2349	weak & direct	<.001 **
	USD Index (reciprocal)	0.0213	very weak & direct	0.639 ns
2009–2018	MYR/USD Exchange Rate	0.3663	weak & direct	<.001 **
	USD Index (reciprocal)	0.0213	very weak & direct	0.291 ns

The Bursa Malaysia KLCI Index had a weak (r = 0.2349) direct linear association to the MYR/USD Exchange rate for the years 2017 to 2018 but shared stronger (r = 0.3663) direct linear association for the past 10 years. Both were found to be statistically significant. On the other hand, its associations to the USD Index, aside from being very weak, were also not significant. This implies that the Bursa Malaysia KLCI Index does not share linear association with USD Index (reciprocal). All associations were positive or direct, which means that when the MYR/USD exchange rate or USD index (reciprocal) increases (or decreases), the Bursa Malaysia KLCI Index also increases (or decreases).

Dependence of Bursa Malaysia KLCI Index: Selection of Lag Order

Table 21. Selected lag order and LR Test p-value for Malaysia

Year Group	Variable	Selected Lag Order	Suggested by:	LR Test p-value
2017–2018	Bursa Malaysia KLCI Index	1	HQIC, SBIC	<.001 **
	MYR/USD Exchange Rate	2	*all four*	<.001 **
	USD Index (reciprocal)	1	*all four*	<.001 **
2009–2018	Bursa Malaysia KLCI Index	2	*all four*	<.001 **
	MYR/USD Exchange Rate	2	HQIC, SBIC	<.001 **
	USD Index (reciprocal)	1	*all four*	<.001 **

For the most recent two years, the Bursa Malaysia KLCI Index and the USD Index (reciprocal) are somehow dictated by the most recent previous value (lag of 1), while the MYR/USD exchange rate is shown to be affected by the two previous values. For the last 10 years, both the Bursa Malaysia KLCI Index and MYR/USD exchange rate are dictated by the two most recent values, while the USD Index (reciprocal) is shown to be affected by the most recent previous value.

Dependence of Bursa Malaysia KLCI Index: Stationary Tests

Table 22. Result of Dicker-Fuller Test on Malaysia

Year Group	Variable	Dickey-Fuller Test p-value: At the level	Dickey-Fuller Test p-value: First-Difference	Remark
2017–2018	Bursa Malaysia KLCI Index	0.417 ns	<.001 **	First-differenced data is stationary.
	MYR/USD Exchange Rate	0.989 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.926 ns	<.001 **	First-differenced data is stationary.
2009–2018	Bursa Malaysia KLCI Index	0.993 ns	<.001 **	First-differenced data is stationary.
	MYR/USD Exchange Rate	0.632 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.490 ns	<.001 **	First-differenced data is stationary.

All variables across different timeframes that were tested showed that their respective time series is a stationary process. This essentially means that the change in Bursa Malaysia KLCI Index is somewhat predictable by the movements in the MYR/USD exchange rate and is not due to "random walk."

Dependence of Bursa Malaysia KLCI Index: Regression Models of Bursa Malaysia KLCI Index

Table 23. Regression result for Malaysia (MYRUSD versus Bursa Malaysia)

	2017–2018		2009–2018	
Predictor	**Coefficient**	**p-value**	**Coefficient**	**p-value**
(L1D). Bursa Malaysia KLCI Index	0.06	0.408 ns	0.06	0.050 **
(L2D). Bursa Malaysia KLCI Index	-	-	-0.02	0.544 ns
(D). MYR/USD Exchange Rate	4639.47	<.001 **	2577.79	<.001 **
(L1D). MYR/USD Exchange Rate	-357.71	0.696 ns	-97.75	0.548 ns
(L2D). MYR/USD Exchange Rate	-45.97	0.960 ns	336.32	0.031 **
R-squared	5.82%		13.86%	

Significant effect was determined in the current change in MYR/USD exchange rate. A unit increase in current change in MYR/USD exchange rate caused an increase of 4639.47 to current change in the Bursa Malaysia KLCI Index in 2017–2018 and an increase of 2577.79 in 2009–2018. This can provide evidence that Bursa Malaysia KLCI Index has linear dependence to MYR/USD exchange rate.

Around 5.82% only of changes in Bursa Malaysia KLCI Index can be explained by the three predictors during 2017–2018. Extending it to the most recent 10 years, the predictors can explain 13.86% of variations in the Bursa Malaysia KLCI Index.

Table 24. Regression result for Malaysia (MYRUSD and USD Index reciprocal versus Bursa Malaysia)

	2017–2018		2009–2018	
Predictor	**Coefficient**	**p-value**	**Coefficient**	**p-value**
(L1D). Bursa Malaysia KLCI Index	0.06	0.378 ns	0.06	0.049 **
(L2D). Bursa Malaysia KLCI Index		-	-0.02	0.551 ns
(D). MYR/USD Exchange Rate	4778.66	<.001 **	2655.89	<.001 **
(L1D). MYR/USD Exchange Rate	-241.48	0.814 ns	29.00	0.866 ns
(L2D). MYR/USD Exchange Rate	-472.05	0.615 ns	334.11	0.040 **
(D). USD Index (reciprocal)	-8183.29	0.480 ns	-9172.82	0.006 **
(L1D). USD Index (reciprocal)	11455.66	0.337 ns	-685.82	0.832 ns
R-squared	6.13%		14.14%	

Incorporating the USD Index (reciprocal) into the model showed that significant effect remained to be determined in the current change in MYR/USD exchange rate. A unit increase in current change in MYR/USD exchange rate caused an increase of 4778.66 to the current change in the Bursa Malaysia KLCI Index in 2017-2018 and an increase of 2655.89 in 2009-2018. This can likewise provide evidence that Bursa Malaysia KLCI Index has linear dependence to MYR/USD exchange rate.

Only around 6.13% of changes in Bursa Malaysia KLCI Index can be explained by the above predictors during 2017–2018. Extending it to the most recent 10 years, the predictors can explain 14.14% of the variations in the Bursa Malaysia KLCI Index.

Results for India

Association of the BSE SENSEX to INR/USD Exchange Rate and USD Index (reciprocal)

Table 25. Correlation coefficients and p-values for India

Year Group	Association of Stock Market to:	Pearson's Correlation Coefficient	Interpretation	p-value
2017–2018	INR/USD Exchange Rate	0.3489	weak & direct	<.001 **
	USD Index (reciprocal)	0.0675	very weak & direct	0.134 ns
2011–2018	INR/USD Exchange Rate	0.3832	weak & direct	<.001 **
	USD Index (reciprocal)	0.0004	very weak & direct	0.985 ns

The BSE SENSEX had a weak (r = 0.3489) direct linear association to INR/USD Exchange rate for the years 2017 to 2018 but shared stronger (r = 0.3832) direct linear association for the past 10 years. Both were found to be statistically significant. On the other hand, its association to USD Index (reciprocal) in both timeframes are both very weak and not significant. This implies that the BSE SENSEX does not share a linear association with the USD Index (reciprocal). All associations were positive or direct, which means that when the INR/USD exchange rate increases (or decreases), the BSE SENSEX also increases (or decreases).

Dependence of BSE SENSEX: Selection of Lag Order

Table 26. Selected lag order and LR Test p-value for India

Year Group	Variable	Selected Lag Order	Suggested by:	LR Test p-value
2017–2018	BSE SENSEX	1	*all four*	<.001 **
	INR/USD Exchange Rate	1	*all four*	<.001 **
	USD Index (reciprocal)	1	*all four*	<.001 **
2011–2018	BSE SENSEX	2	*all four*	0.001 **
	INR/USD Exchange Rate	3	FPE, AIC, HQIC	0.001 **
	USD Index (reciprocal)	2	FPE, AIC, HQIC	0.020 **

For the most recent two years, the BSE SENSEX, INRUSD exchange rate, and USD Index (reciprocal) are somehow dictated by the most recent previous value (lag of 1). For the last eight years, both the BSE SENSEX and the USD Index are dictated by the two most recent values, while the INR/USD exchange rate is shown to be affected by the three most recent values.

Dependence of BSE SENSEX: Stationary Tests

Table 27. Result of Dicker-Fuller Test on India

Year Group	Variable	Dickey-Fuller Test p-value: At the level	First-Difference	Remark
2017–2018	BSE SENSEX	0.974 ns	<.001 **	First-differenced data is stationary.
	INR/USD Exchange Rate	0.726 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.944 ns	<.001 **	First-differenced data is stationary.
2011–2018	BSE SENSEX	0.582 ns	<.001 **	First-differenced data is stationary.
	INR/USD Exchange Rate	0.987 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.811 ns	<.001 **	First-differenced data is stationary.

All variables across different timeframes that were tested showed that their respective time series is a stationary process. This essentially means that the change in the BSE SENSEX is somewhat predictable by the movements in the INR/USD exchange rate and is not due to "random walk."

Dependence of BSE SENSEX: Regression Models of BSE SENSEX

Table 28. Regression result for India (INRUSD versus BSE SENSEX)

Predictor	2017-2018 Coefficient	2017-2018 p-value	2011-2018 Coefficient	2011-2018 p-value
(L1D). BSE SENSEX	0.04	0.497 ns	0.05	0.055 **
(L2D). BSE SENSEX	-	-	-0.03	0.249 ns
(D). INR/USD Exchange Rate	1573548.00	<.001 **	1055073.00	<.001 **
(L1D). INR/USD Exchange Rate	-9195.62	0.965 ns	-8908.05	0.892 ns
(L2D). INR/USD Exchange Rate	-	-	70482.62	0.264 ns
(L3D). INR/USD Exchange Rate	-	-	132600.10	0.024 **
R-squared	12.33%		15.38%	

Significant effect was determined in the current change in INR/USD exchange rate. A unit increase in current change in the INR/USD exchange rate caused an increase of 1573548.00 to current change in the BSE SENSEX in 2017-2018 and an increase of 1055073.00 in 2009-2018. This can provide evidence that the BSE SENSEX has linear dependence to the TRY/USD exchange rate.

Only around 12.33% of changes in BSE SENSEX can be explained by the three predictors during 2017–2018. Extending it to the most recent 10 years, the predictors can explain 15.38% of variations in the BSE SENSEX.

Table 29. Regression result for India (INRUSD and USD Index reciprocal versus BSE SENSEX)

Predictor	2017–2018 Coefficient	2017–2018 p-value	2011–2018 Coefficient	2011–2018 p-value
(L1D). BSE SENSEX	0.04	0.492 ns	0.05	0.056 **
(L2D). BSE SENSEX	-	-	-0.03	0.218 ns
(D). INR/USD Exchange Rate	1599073.00	<.001 **	1120737.00	<.001 **
(L1D). INR/USD Exchange Rate	34645.80	0.872 ns	26361.22	0.711 ns
(L2D). INR/USD Exchange Rate	-	-	84261.07	0.208 ns
(L3D). INR/USD Exchange Rate	-	-	137791.70	0.020 **
(D). USD Index (reciprocal)	-125281.40	0.602 ns	-445374.10	<.001 **
(L1D). USD Index (reciprocal)	-168917.50	0.507 ns	-94560.75	0.364 ns
(L2D). USD Index (reciprocal)	-	-	-57774.91	0.541 ns
R-squared	12.44%		16.42%	

Incorporating the USD Index (reciprocal) into the model showed that significant effect remained to be determined in the current change in INR/USD exchange rate. A unit increase in the current change in the INR/USD exchange rate caused an increase of 1599073.00 to the current change in the BSE SENSEX in 2017–2018 and an increase of 1120737.00 in 2011–2018. This can likewise provide evidence that BSE SENSEX has linear dependence to the INR/USD exchange rate.

Only around 12.44% of changes in BSE SENSEX can be explained by the above predictors during 2017–2018. Extending it to the most recent eight years, the predictors can explain 16.42% of variations in the BSE SENSEX.

Results for Turkey

Association of Borsa Istanbul 100 Index to TRY/USD Exchange Rate and USD Index (reciprocal)

Table 30. Correlation coefficients and p-values for Turkey

Year Group	Association of Stock Market to:	Pearson's Correlation Coefficient	Interpretation	p-value
2017–2018	TRY/USD Exchange Rate	0.3556	weak & direct	<.001 **
	USD Index (reciprocal)	0.1675	very weak & direct	<.001 **
2009–2018	TRY/USD Exchange Rate	0.3624	weak & direct	<.001 **
	USD Index (reciprocal)	0.1192	very weak & direct	<.001 **

The Borsa Istanbul 100 Index had a weak (r = 0.3556) direct linear association to the TRY/USD Exchange rate for the years 2017 to 2018 but shared stronger (r = 0.3624) direct linear association for the past 10 years. Both were found to be statistically significant. On the other hand, its association to the USD Index (reciprocal) in both timeframes is very weak but nonetheless significant. This implies that the Borsa Istanbul 100 Index does share to some degree a linear association with the USD Index (reciprocal). All associations were positive or direct, which means that when the TRY/USD exchange rate or the USD index (reciprocal) increases (or decreases), the Borsa Istanbul 100 Index also increases (or decreases).

Dependence of Borsa Istanbul 100 Index: Selection of Lag Order

Table 31. Selected lag order and LR Test p-value for Turkey

Year Group	Variable	Selected Lag Order	Suggested by:	LR Test p-value
2017–2018	Borsa Istanbul 100 Index	1	*all four*	<.001 **
	TRY/USD Exchange Rate	4	FPE, AIC, HQIC	0.020 **
	USD Index (reciprocal)	1	*all four*	<.001 **
2009–2018	Borsa Istanbul 100 Index	1	*all four*	<.001 **
	TRY/USD Exchange Rate	4	*all four*	0.001 **
	USD Index (reciprocal)	1	*all four*	<.001 **

For the most recent two years, the Borsa Istanbul 100 Index and the USD Index (reciprocal) are somehow dictated by the most recent previous value (lag of 1), while the TRY/USD exchange rate is shown to be affected by the four previous values. For the last 10 years, both the Borsa Istanbul 100 Index and the USD Index are dictated by the most recent value, while the TRY/USD exchange rate is shown to be affected by the four most recent values.

Dependence of Borsa Istanbul 100 Index: Stationary Tests

Table 32. Result of Dicker-Fuller Test on Turkey

Year Group	Variable	Dickey-Fuller Test p-value		Remark
		At the level	First-Difference	
2017–2018	Borsa Istanbul 100 Index	0.877 ns	<.001 **	First-differenced data is stationary.
	TRY/USD Exchange Rate	0.652 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.939 ns	<.001 **	First-differenced data is stationary.
2009–2018	Borsa Istanbul 100 Index	0.903 ns	<.001 **	First-differenced data is stationary.
	TRY/USD Exchange Rate	0.601 ns	<.001 **	First-differenced data is stationary.
	USD Index (reciprocal)	0.488 ns	<.001 **	First-differenced data is stationary.

All variables across different timeframes that were tested showed that their respective time series is a stationary process. This essentially means that the change in Borsa Istanbul 100 Index is somewhat predictable by the movements in the TRY/USD exchange rate and is not due to "random walk."

Dependence of Borsa Istanbul 100 Index: Regression Models of Borsa Istanbul 100 Index

Table 33. Regression result for Turkey (TRYUSD versus Borsa Istanbul)

	2017–2018		2009–2018	
Predictor	**Coefficient**	**p-value**	**Coefficient**	**p-value**
(L1D). Borsa Istanbul 100 Index	0.01	0.903 ns	-0.08	0.004 **
(D). TRY/USD Exchange Rate	157071.60	<.001 **	101407.30	<.001 **
(L1D). TRY/USD Exchange Rate	-20281.53	0.450 ns	17330.87	0.003 **
(L2D). TRY/USD Exchange Rate	3030.97	0.882 ns	-4339.60	0.391 ns
(L3D). TRY/USD Exchange Rate	-24735.01	0.156 ns	-1031.25	0.827 ns
(L4D). TRY/USD Exchange Rate	11432.70	0.522 ns	-5184.45	0.290 ns
R-squared	13.17%		13.90%	

Significant effect was determined in the current change in the TRY/USD exchange rate. A unit increase in current change in TRY/USD exchange rate caused an increase of 157071.60 to the current change in the Borsa Istanbul 100 Index in 2017–2018 and an increase of 101407.30 in 2009–2018. This can provide evidence that the Borsa Istanbul 100 Index has linear dependence to the TRY/USD exchange rate.

Only around 13.17% of changes in the Borsa Istanbul 100 Index can be explained by the three predictors during 2017–2018. Extending it to the most recent 10 years, the predictors can explain 13.90% of variations in the Borsa Istanbul 100 Index.

Table 34. Regression result for Turkey (TRYUSD and USD Index reciprocal versus Borsa Istanbul)

	2017–2018		2009–2018	
Predictor	**Coefficient**	**p-value**	**Coefficient**	**p-value**
(L1D). Borsa Istanbul 100 Index	-0.004	0.946 ns	-0.08	0.005 **
(D). TRY/USD Exchange Rate	148116.60	<.001 **	108792.00	<.001 **
(L1D). TRY/USD Exchange Rate	-20644.26	0.468 ns	19100.34	0.006 **
(L2D). TRY/USD Exchange Rate	4007.38	0.844 ns	-4058.99	0.422 ns
(L3D). TRY/USD Exchange Rate	-23985.19	0.169 ns	-805.70	0.865 ns
(L4D). TRY/USD Exchange Rate	11836.40	0.507 ns	-5431.19	0.270 ns
(D). USD Index (reciprocal)	1969789.00	0.148 ns	-1053689.00	0.010 **
(L1D). USD Index (reciprocal)	897357.40	0.515 ns	-272519.20	0.472 ns
R-squared	13.60%		14.18%	

Incorporating the USD Index (reciprocal) into the model showed that significant effect remained to be determined in the current change in the TRY/USD exchange rate. A unit increase in the current change in TRY/USD exchange rate caused an increase of 148116.60 to the current change in the Borsa Istanbul 100 Index in 2017–2018 and an increase of 108792.00 in 2009–2018. This can likewise provide evidence that the Borsa Istanbul 100 Index has linear dependence to the TRY/USD exchange rate.

Only around 13.60% of changes in the Borsa Istanbul 100 Index can be explained by the above predictors during 2017–2018. Extending it to the most recent 10 years, the predictors can explain 14.18% of variations in the Borsa Istanbul 100 Index.

Results for MSCI Emerging Markets

Correlation of MSCI Emerging Markets Index to MSCI EM Currency Index

Table 35. Correlation coefficients and p-values for MSCI EM Index vs. MSCI EM Currency Index

Year Group	**Pearson's Correlation Coefficient**	**Interpretation**	**p-value**
2017–2018	0.9418	very strong & direct	<.001 **
2015–2019	0.9673	very strong & direct	<.001 **

The MSCI Emerging Markets Index had a very strong (r = 0.9418) direct linear association to the MSCI EM Currency Index rate for the years 2017 to 2018 and shared an even stronger (r = 0.9673) direct linear association for the past five years. Both were found to be statistically significant. This implies that the MSCI Emerging Markets Index shares to a huge degree a linear association with the MSCI EM Currency Index. All associations were positive or direct, which means that when MSCI EM Currency Index increases (or decreases), the MSCI Emerging Market Index also increases (or decreases).

Dependence of MSCI Emerging Markets Index to MSCI EM Currency Index

Table 36. Regression result for MSCI EM Index versus MSCI EM Currency Index

Predictor	2017–2018		2015–2019	
	Coefficient	**p-value**	**Coefficient**	**p-value**
(L1D). MSCI Emerging Market Index	0.11	0.011 **	0.10	0.002 **
(L2D). MSCI Emerging Market Index	0.05	0.101 ^{ns}	-0.02	0.542 ^{ns}
(D). MSCI EM Currency Index	1.34	<.001 **	1.29	<.001 **
(L1D). MSCI EM Currency Index	-0.13	0.136 ^{ns}	-0.08	0.161 ^{ns}
(L2D). MSCI EM Currency Index	-	-	0.09	0.114 ^{ns}
(L3D). MSCI EM Currency Index	-	-	0.03	0.452 ^{ns}
R-squared	46.91%		53.74%	

Significant effect was determined in the current change in the MSCI EM Currency Index. A unit increase in the current change in the MSCI EM Currency Index caused an increase of 1.34 to the current change in the MSCI Emerging Markets Index in 2017–2018 and an increase of 1.29 in 2015–2019. This can provide notable evidence that MSCI Emerging Markets Index has linear dependence to the MSCI EM Currency Index.

Around 46.91% of the changes in the MSCI Emerging Markets Index can be explained by the two predictors during 2017–2018. Extending it to the most recent five years, the predictors can explain 53.74% of variations in the MSCI Emerging Markets Index.

Tally of "Signals" generated from the MSCI EM Currency Index

Figure 1. Chart of MSCI EM Index versus MSCI EM Currency Index (Jan. 12, 2015, to April 1, 2019)

Using the daily data from January 12, 2015, to April 1, 2019, it was found that there were 17 instances where the MSCI EM Currency Index declined by 2% from an established swing high. With approximately 20 trading days of duration, the said 2% or so drop in MSCI EM Currency Index translated to an average 4.64% decline in the EM equity index in the same period. The MSCI EM Index continued to decline by another 1.10% on average in the succeeding month. Two months post the 2% dip in the currency basket, the EM equity index has remained weak, dropping by another 1.34% on average. Three months post the 2% dip in the currency basket, the EM equity index was down by an average of 3.67% on top of its initial decline.

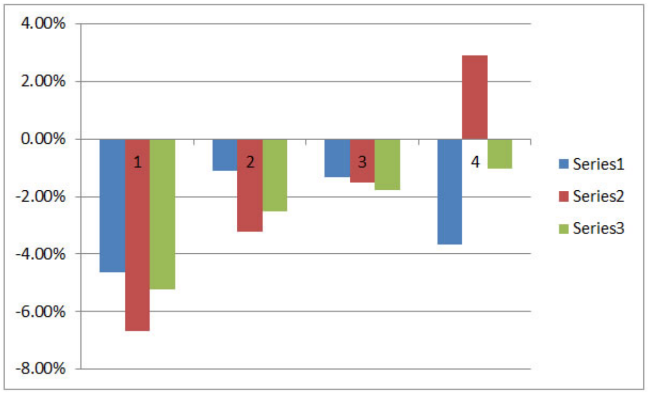
There were also 14 instances where the MSCI EM Currency Index broke down by 2% from an established swing low. With approximately 44 trading days in duration, the said 2% or so slip in the EM currency basket translated to an average 6.69% decline in the EM equity index in the same period. The EM equity index continued to falter by another 3.22% on average in the succeeding month. Two months post the 2% dip from the swing low of the currency basket, the EM equity index has mildly recovered but remained down by another 1.53% on average. Three months post the 2% dip in the currency basket, the EM equity index rallied by 2.92% on average from its low on the 44th day.

In the 31 instances where the MSCI EM Currency Index declined by 2% or so from both swing high and swing low with an average duration of 30 trading days, the MSCI Emerging Markets Index consequently declined by an average of 5.22% in the same period. The EM equity index continued to weaken by another 2.51% on average one month after. In the two months after the 2% dip in the currency basket, the EM equity index recovered a bit but remained down by another 1.78%. In the three months after the 2% dip in the currency basket, the EM equity index continued to recover but nonetheless remained down by 1.02% on average on top of its initial slip.

Table 37. Percentage changes following swing high declines and swing low breaks (MSCI)

				% Decline in EM Equities			
2% Slip in EM Currency Index	# Signals	Duration in Days		During	1 Month After	2 Months After	3 Months After
Swing High Decline	11	19.82		-4.64%	-1.10%	-1.34%	-3.67%
Swing Low Break	8	44.25		-6.69%	-3.22%	-1.53%	2.92%
Total	19	30.11		-5.22%	-2.51%	-1.78%	-1.02%

Figure 2. Graph of % changes in EM equities following swing high declines and swing low breaks



Discussion

This paper provided an argument and ample evidence to support the use of the changes in the Asian emerging market currencies as signals for forecasting consequent changes in their respective equity markets. While from the correlation analysis that was used covering the periods of the last one year and the last 8 to 10 years showed a weak linear relationship between the domestic Asian currencies against their respective equity indices, their association nonetheless remained statistically significant. The analysis and the results of the "signals" that were generated actually supports the findings of Usman Umer *et al.* in that the "comovements between exchange rates and stock prices become stronger during the crises time" or when there was an increased volatility in the exchange rate in the short run. It was determined that the sensitivity or beta of equities from the movement in the exchange rate can be as much as 2.6 times. Furthermore, it was also seen that the resulting weakness in equities have not just persisted but even deepened in the succeeding one to three months. One may therefore use a "breakdown" in the domestic currency as a signal to hedge against a possible drop of as much as 10% in the respective domestic equities in the next two and half months. Additionally, it was determined that the association and proportion of the variance (R squared) between domestic currencies and equity markets notably improve with longer historical data of 8 to 10 years relative to a year's data alone.

Conclusion

For the periods covering the last 8 to 10 years, the stationary tests that were done all showed that the sample Asian equity indices were to a certain degree predictable by the movements in their domestic currency and, more importantly, that their movements were not due to "random walk." It was also found that significant effect was determined in the current change in the domestic currencies vis a vis their respective equity index using regression analysis. While the changes in the currency only explain as low as 2.58% in the past year that was tested and 5.78% in the past eight years the changes in the equity index as in the case of Thailand, the dependence can be found much higher in Indonesia, Malaysia, India, and Turkey. Meanwhile, the correlation and regression analyses done in the MSCI EM Currency Index against the MSCI EM Index actually found a very strong direct correlation of at least 94%, while the former could explain as much as 53% of the changes in the latter. Even if the changes in the currency only explains 12–14% of the changes in its respective equities covering 8 to 10 years, the author deems that such is already heavy enough to warrant a closer analysis of the movements in the exchange rate when actively managing a domestic equity portfolio. Adverse domestic currency movements can indeed be used as an indicator of a potential earthquake in the corresponding equity space both in the one to three months ahead and in the long run.

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Coefficient Moving Average

By Mohamed Fawzy ElSayed Ali AbdAlla, CETA, CFTe, MFTA

Mohamed Fawzy ElSayed Ali AbdAlla, CETA, CFTe, MFTA

+201005004322
fawzyuro@gmail.com

Abstract

Data averaging is not only one of the most important but also the most commonly used tool in all money-related fields; from upwards to downwards, it is used in econometrics to analyse a country's macro-economic factors. It is also applicable to fundamental and technical analysis for financial ratios and price charts of sectors and companies. Data average is performed by many different types and techniques; the most used and popular are the simple arithmetic, the geometric, the weighted, and the exponential average. Comparing a sequence of successive averages is known as moving average.

Before using a popular tool and depending on its outcome, it is logically mandatory to understand deeply the advantages and disadvantages of each type of moving average. The majority of technicians consider the exponential moving average (EMA) to be the most suitable and efficient average in terms of its concept, which some believe to be a myth. Moreover, the EMA is embedded in the calculation of many popular technical indicators and is used by technicians in coding the formula of their developed indicators.

This paper will attempt to deeply understand the drawbacks of the EMA and introduce the the coefficient moving average (CMA)—a moving average with a new concept in its calculation that is thought to be a better combination, with more real advantages and fewer disadvantages than other well-known moving averages. Besides, CMA is more flexible and able to be adjusted by the user to fit its intended use.

Introduction

Overview on Moving Averages in Technical Analysis

Moving averages seem to be the most successful tool in the objective of technical analysis—mainly because averages as lagging indicators profit from the trend by allowing entry and exit points after sufficient confirmation and dampen the effects of short-term oscillations. Additionally, the averages are essential components in the calculation of almost all other indicators and oscillators, e.g., MACD, Stochastic, CCI, ADX, RSI (Kirkpatrick, 2016).

Therefore, it is mandatory to fully understand the drawbacks of each of the most commonly used moving averages—simple, weighted, and exponentia—to know how much we were misled due to their limitations and how restricted we were in our choices.

Popular Commonly Used Moving Averages (SMA, WMA, EMA)

The simple moving average (SMA), also named truncated moving average, is the real average of the data over the period as being the arithmetic mean, which is equal to the summation of the data divided by the number of the data.

$$SMA(t) = \Sigma(Pi) / n$$

Where Pi is the price at a time point (i), n is the number of prices or the time points.

However, SMA has disadvantages:

1. It gives equal weights to all the data from the recent significant datum until the old less important datum.
2. It is affected by extreme value, as only one extremely larger or extremely smaller value will drag the average to it and away from the rest of the repeating values. This disadvantage occurs twice; first, when the extreme value has recently come into the average window, and second, when it is late to drop off the period of the average. Mainly, when it exists, the average causes a lot of misleading average movmente. This flaw is worse with a shorter moving average (Alexander Elder, 2014).
3. It does not contain the historical data.

The weighted moving average (WMA) gives less weight (=1) to the oldest datum in the period that increases regularly (by +1) until the most important recent datum in the period.

$$WMA(t) = \Sigma(Pi.Wi) / n$$

Where Pi is the price at a time point (i), Wi is the weight of the price Pi, n is the number of prices or the time points.

Therefore, WMA overcomes the disadvantages of not giving more importance to the recent data. In addition, the extreme value will greatly affect the average only when entering it, which is accepted, but its weight will decrease gradually until exiting the average unnoticed. However, the WMA still does not contain the historical data as with the SMA.

The exponential moving average (EMA) not only gives more importance to the recent data but also contains the historical data.

$$EMA(t) = [\ K\ .P(t)\ ] + [\ (1\text{-}K)\ .EMA(t\text{-}1)\ ]$$
$$K = 2 / (n\text{-}1)$$

Where K is the smoothing coefficient of the EMA, P(t) is the price at a time of EMA, EMA(t-1) is the previous EMA, n is the period of the average. Huston has described the smoothing constant "k" (Perry Kaufman, 2013).

Weighted and Exponential Moving Averages Explained

Digging Deeper Into WMA Misses

The WMA is weighted by multiples of the weight of the oldest datum, which is acceptable. The progress of the cumulative weight for the data weights of a WMA with a period of 100, starting from the highest weight of the most recent datum (100) and cumulating to the smallest weight of the oldest datum (1), is illustrated in Table 1 and is compared to the linear progressing cumulative weight of SMA in Figure 1.

Table 1. The relation between the number of datum and the percentage completed from the whole weights of WMA

Number of Datum	Completed % of the WMA weights	Number of Datum	Completed % of the WMA weights
14	25.9%	43	67.3%
19	34.2%	51	75.7%
25	43.6%	67	88.9%
30	50.8%	75	93.6%
34	56.2%	91	99.1%

Figure 1. The progress of the cumulative weight for a WMA 100 compared to that of the equal weights SMA 100

Therefore, it is evident, for example, that half the data contributes to three-quarters the weight of the average and the oldest tenth of data is nearly neglected. Besides, it is worthy to note that the data in the previous table and chart also applies for WMA with periods of 20 or more, and near figures are obtained for WMA with periods of 3 to 19. Those results reveal a new disadvantage of the WMA: its weighting technique seems to be *overweighted* and biased significantly to the recent data. Moreover, there are no other weighting options between the unweighted SMA technique and the overweighted WMA technique.

Digging Deeper Into EMA Misses

In this section, we will explain in detail the EMA using the methodology of applying logical questions and showing the surprising answers that will all together expose the fragility of the EMA technique.

Question 1: What does the (K) factor in the EMA equation stands for?

For the WMA of the period (n):

The weight of the current datum (highest weight of the most recent datum) is = n / Σ weights

The weight of the datum previous to most recent datum is = (n-1) / Σ weights

The weight of the oldest datum (smallest weight) is = 1 / Σ weights.

And since the weights are the arithmetic series of the natural numbers "1, 2, 3, 4, 5, ... , n" its summation is $= (n^2+n)/2 = (n * (n+1)) / 2$.

Thus, the weight of the current datum = $n / [(n * (n+1)) / 2] = 2n / (n * (n+1) = 2/(n+1)$, which is equal to the "K" constant used in the EMA calculation.

The earlier conclusion means that in the EMA technique:

1. The weight of the most recent datum for the WMA and EMA are equal, and both are equal to 2/(n+1) which is the (K).
2. In the WMA, the weight of the previous datum is calculated again by decreasing rate and so on until the oldest datum takes the weight of $2 / (n^2+n)$. While in the EMA, the weight of the previous datum is the same as the weight of the first datum, but it is calculated from the residual of the average weights. And so on, until the oldest datum of the period takes the weight from the last residual of the average weights, and then the left is set for the historical data weight (data from the start of the chart until before the calculated period).
3. Accordingly, the weight of the historical data takes nothing from the weight of the most recent datum in the EMA if compared to the weight of the current datum in the similar WMA.

Question 2: What is the weight of the historical data (before the period) in the average weight?

By understanding the calculation of the EMA; where the recent datum takes (K) weight, and the previous average takes (1-K) weight. From the weight of the previous average, which is (1-K), again the before previous datum takes (K) weight and the before previous average takes (1-K) weight. And so on, this process is repeated until the oldest datum in the period takes (K) weight, and the last residual (1-K) weight is left for the data before the average period, which stands for all the previous historical data before the EMA period.

Thus, this final residual weight is the residual from the residual from the residual and so on, which is equal to (1-k) from (1-k) from (1-k) and so on for (n) loops. Therefore, it is concluded that we can calculate the weight of the historical data in the EMA by the equation:

$$W(H) = (1-k)^n = [1- (2/(n+1))]^n$$

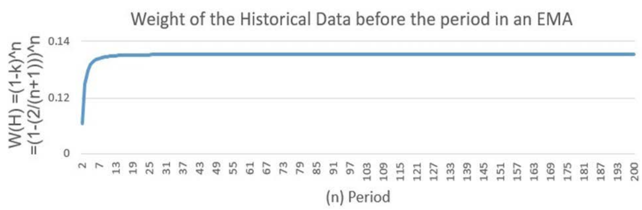
Where W(H) is the weight of the historical data before the (n) period of the EMA.

By this equation, we can plot a curve displaying the weights of the historical data before the period in an EMA against all periods of EMA from 2 to 200; the resulting data showed that the historical data always has 13.5% weight of the EMA. Moreover, the curve turned out to look like an exponential curve that may be the origin of the name of the average. This is illustrated in Table 2 and Figure 2.

Table 2. The weight of the historical data before the period in an EMA

Period (n) of EMA	W(H) = (1-k)^n = (1-(2/(n+1)))^n
2	11%
3	12.5%
4	13%
14	13.4%
17	13.5%
200	13.53%

Figure 2. The weight of the historical data before the period in different EMA



Knowing the weight of the historical data as a percentage is a good issue, but the most important is knowing its relative weight to other data weights in the average. To start, we have to standardize an allocation system for the data in the average, so we will consider the location (L) of the most recent current datum as "0" and the previous datum as "1" and so on till the oldest datum in the period having a location of "n-1". Therefore, we can calculate the weight (W) of any location (L) in a WMA with any period (n) by the following equation:

W(L) in WMA(n) = [2* (n-L)] / [n*(n+1)]

And for the EMA: W(L) = K * (1-k)^L and since 1-k = (n+1 / n+1) – (2 / n+1) = n-1 / n+1 so W(L) in EMA(n) = (2/n+1) * [(n-1/n+1)^L] = (2/ n+1) * [(n-1)^L / (n+1)^L] so finally:

W(L) in EMA(n) = [2 * ((n-1)^L)] / [(n+1)^(L+1)]

By applying these equations to different locations and the historical data in different EMA of different periods, we will find surprising drawbacks in the weighting system of the EMA as following:

1. The weight of the historical data before the period may be more than the weight of the oldest datum in the period; this occurs very early in the period of (4):
   EMA(3): W(0)=50%, W(1)=25%, W(2)=12.5%, W(H)=12.5% so W(H)=W(oldest).
   EMA(4): W(0)=40%, W(1)=24%, W(2)=14.4%, W(3)=8.64%, W(H)=12.96% so W(H)>W(oldest).
2. Moreover, the weight of the historical data before the period may be more than the weight of the most recent (most important) current datum in the period; this occurs early in the period of (14). The relation between them in different EMA periods are illustrated in Table 3.

Table 3. The relation between the weight of current datum and the weight of historical data in different periods of EMA

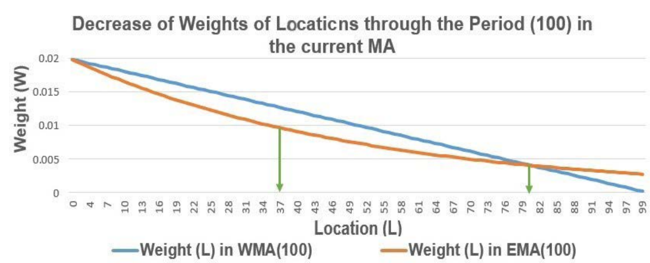
Period (n) of EMA	Weight of current datum W(0)	Weight of historical data W(H)	Ratio W(H):W(0)
13	14.28%	13.48%	<
14	13.33%	13.49%	>
20	9.52%	13.51%	1.42 times
50	3.92%	13.53%	3.45 times
100	1.98%	13.53%	6.83 times
200	0.99%	13.53%	13.66 times

Question 3: From where and how are the 13.5% weight of the historical data obtained from the weights of the data in the EMA period?

For the WMA, the weight of the current datum is the highest, and then the weights decrease regularly (with fixed value = weight of the oldest datum) until the lowest weight of the oldest datum to cumulatively form 100% of the WMA weights. While for the EMA, the weight of the current datum is the highest (= weight of current datum in WMA), and then the weights decrease *irregularly* (with increasing rate then decreasing rate) until the lowest weight of the oldest datum to cumulatively form 86.46% of the EMA weights.

For the EMA, the weights of the data in the period show chronological decreasing rate, as illustrated in Figure 3.

Figure 3. The irregular decrease in weights through locations in the EMA



1. During the recent 36% of the data (from the most recent current datum backwards to third the data), a rapid decrease in weights occurs to form cumulatively 52.29% of average weights. Also the weights are less than their similar locations in the WMA where the difference reachs its maximum at the end of this partition.
2. From 37% to 79% of the data (middle 43% of data), a slow decrease in weights occurs. At the end of this portion, the cumulative weight reaches 79.81% of the average weights. Also the weights are less than their similar locations in the WMA, where at the end of this partition the cumulative weight is equal in EMA and WMA.
3. From 80% to the oldest datum (oldest 21% of data), a very slow decrease in weights occurs. At the end of this portion, the cumulative weight reaches 86.46% of the average (and 13.54% is left to the historical data before the period). Also the weights are more than their similar locations in the WMA.

Therefore, it is obvious that the weight of the historical data (13.5%) are obtained irregularly from the weights of the data in the period causing an irregular rate of decrease in the weights of the data in the period. In fact, this is because the decrease in the weights is by a regular percentage rate not a value rate, where this percentage rate of decrease is equal to (K). Therefore, each location weight is less than the previous location weight by K% of that previous location weight. So, EMA is a percentage smoothing average.

Question 4: How far does the EMA go in history?

Theoretically and mathematically, the SMA for the oldest period in the early beginning of the data has a calculated weight in the recent EMA occurring after many decades of data. But practically speaking, the weight of the EMA is divided into 86.46% to the recent period and 13.54% to all the previous data, where this 13.54%, in turn, is divided into 86.46% of it to the previous period, and 13.54% of it is left to the data before the recent two periods, and so on. The cumulative weight of periods of data in the EMA is illustrated in Table 4.

Table 4. The cumulative weight of previous periods in EMA

Previous periods of data	Cumulative weight in current EMA
1	86.46%
1.5	95.02%
2	98.17%
2.3	99.01%
3	99.75%
3.5	99.91%
4.5	99.99%

This result uncovers the fact that the EMA considers (nearly only) the recent two and third periods of data and does not handle the aggregate historical data.

Question 5: What does the EMA actually perform in the period?

The EMA does not perform any specific action on the data in the period other than that on the data before the period. So in fact, the EMA does not respect the period at all. It seems that the EMA misleads the user by entering a value in a data field called "EMA Period"; while this value will not be used as its name, the EMA uses the period value only to create a smoothing factor (K) simulating the first weight in the WMA with a period like the entered value. Afterwards, the EMA uses this generated "constant" to smooth all the data, disregarding the data in the period from the data before the period and giving no advantage to the data in the period.

Therefore, the EMA really does not "average" the data in a specific period like SMA and WMA but smoothes all the data. Also, each SMA or WMA at a new point in time considers a new datum and neglects an old datum, so actually it "moves" through the data. However, each EMA at any point in time smoothes the all the data before it, so it is misnamed as "moving" and as "average" too.

The SMA can be officially named "moving arithmetic mean", and the WMA is best named as "weighted moving average". As a point of view, it is more apt to describe the EMA as "exponential smoother" rather than "exponential moving average".

Question 6: What does the EMA actually perform on every data feed?

The EMA does not deserve the name average, as it acts only on the current new feed by giving it (K) weight, and it does not consider averaging it with the data in the period preceding it (depending on being included in the previous EMA). So the residual weight is easily directed toward the previous EMA, and so on through the entire data.

For the SMA and the WMA, with every new feed, the oldest datum in the previous average is neglected, and the new feed is averaged again with the other data on a statistical concept of arithmetic mean or weighted mean, so the non-used portion of the current datum is dismissed due to the averaging, which has a tremendous psychological consideration.

However, EMA is not an average; therefore, we will look to it from another view than the weights in an average. So with every new feed, the vertical amplitude between the previous EMA and the current new feed is calculated, the new EMA moves in the direction of the new datum by (K) percentage of this distance, and the residual of the distance is thrown with no statistical bases and without any psychological rational. The user may not understand that the EMA does nothing except slow the entire chart by following the data line and covering only a certain percentage of the lag in each step.

Question 7: When does the EMA deflect?

Since the calculation of the current EMA takes a certain percentage from the current datum and the remaining percentage from the previous EMA, by logic, the current EMA must be located between the current datum and the previous EMA and can not break beyond the current datum or the previous EMA. Accordingly, when the current datum is higher than the previous EMA, the current EMA will rise higher than the previous EMA, disregarding if the current datum is rising or in the same level or declining relative to its previous datum.

Now we can conclude that the rising EMA will never reverse downwards except when crossed by its data to the downside (i.e., the current data is lower than the previous EMA). Then, the current EMA will turn to decrease the downward distance between the EMA line and the data line (the EMA line reverses only after crossed over by its data line). Unlike the smart SMA or WMA, when the current datum is higher than the previous average, but the current datum is much lower than its previous datum, this extreme value (especially in WMA) will significantly affect the current average, so that the current average may be lower than the previous average. Therefore, the moving average reversal can occur before the occurrence of actual (late) crossover of the current datum below the previous EMA. Finally, we can describe the EMA as a slow follower, which resembles an idiot slowly dog walking towards his master who rides a horse.

All these answers now uncover the major mathematical and technical disadvantages of the EMA:

1. It considers almost only an additional 1.3 period of the historical data.
2. This historical data has a weight more than the weight of the current datum in periods greater than 13.
3. The decrease in weights of the data through the period is irregular.
4. It does not consider the period by any specific action.
5. It is not an average to the period but a smoother to the entire data.
6. It is a slow follower (reverse only after crossed over by its data line).

Coefficient Moving Average (CMA)

Calculation and Concept of CMA

Two user-entered parameters are the data array to be averaged (D) and the period of averaging (n). Each average value will act on (n+1) number of data, arranged as follows: the CMA of the previous period, then the oldest datum in the period. Then, proceed chronologically forward until the most recent current datum. Other two user-entered parameters are the value of averaging coefficient (C), ranging from "0" to "1", and the type of averaging (T), which is either simple "0" or compound "1".

- The CMA of the previous period is given a weight of (1).
- When simple averaging is selected, summation is used: weight of each datum = weight of previous datum + coefficient.
- When compound averaging is selected, multiplication is used: weight of each datum = weight of previous datum * (1 + coefficient).
- The current CMA is calculated like the WMA: Current CMA = summation of weighted data / summation of weights.

The weighting system is clarified by an example in Table 5.

Table 5. Example for CMA weighting system

Data (D) = C "closing price", Period (n) = 5, Coefficient (C) = 0.5							
	CMA of previous period	**1** *(oldest datum in period)*	**2**	**3**	**4**	**5** *(current datum in period)*	**Total weights**
Simple CMA (C,5,0.5,0)	1	1.5	2	2.5	3	3.5	13.5
Compound CMA (C,5,0.5,1)	1	1.5	2.25	3.375	5.063	7.594	20.782

At the beginning of the data:

In the oldest period, from the oldest datum until the datum before the most recent, there is no calculated CMA.

In the period after the oldest period, starting from the most recent datum in the first period until the datum before the most recent datum in the second period, the CMA is calculated for (n) data (not n +1)—i.e., without previous CMA, with the oldest datum in the period taking the weight of (1), and the coefficient augments the weights through the period.

Starting from the most recent datum in the second period until the end of the data, CMA is calculated normally.

Advantages of CMA

1. When using the simple averaging method of CMA and selecting a coefficient zero, this simulates the SMA, as all data have equal weights, but with the edge of *including the historical data.*
2. When using the simple averaging method of CMA and selecting a coefficient one, this simulates the WMA, but with the edge of *including the historical data*. Taking advantage over the simple CMA with coefficient zero as being weighted and affected by extreme values only upon entering the average.
3. When using the simple averaging method of CMA and selecting a coefficient between zero and one, this breaks the cuffs and opens the horizon for the user to customise his own suitable regular tested weighting intervals between the unweighted SMA and the overweighted WMA.
4. CMA is a real average that not only *greatly considers the averaged period* but also *includes historical data* in the form of the averaged previous period value, then calculates the *statistically logical* arithmetic or weighted mean. The previous average also contains the before previous average and so on, so CMA is smart to track its own way backwards in the historical data by including only its average before the period.
5. Regarding the depth of the significant considered history, at least one previous period from the historical data is guaranteed, as it is already logically embedded in the averaging mathematical equation, while theoretically all the historical data are included.
6. In addition to including the historical data, CMA ensures:
   a) The decrease in weights of data as we go backwards is not only *regular* but also user-customised.
   b) The weight of the historical data is definitely less than the weight of the oldest datum in any averaged period.
   c) A continuous regular dilation of weights is performed through the data in the averaged period, and then through the historical data.
7. The compound averaging method of the CMA allowed a *regular percentage weighting system* (not as the regular value weighting system of the simple CMA) that also averaged a considered period and added the historical data with the least weight.

CMA Amibroker Formula Language (AFL) Code

Indicator Inputs

```
AveragedData = ParamField("Data Field",3);
Period = Param("Period", 14, 2, 300, 1, 14);
Coefficient = Param("Weight Coefficient", 0.5, 0, 2, 0.01, 0.1);
WeightType = ParamToggle("Weight Type", "Simple|Compound", 0);
```

Calculate Weights and Total Weights

```
Weight[0] = 0; TotalWeights = 0; TotalWeightsWithoutHistory = 0;
for ( Multiplier = 0; Multiplier <= Period; Multiplier++ )
 { if ( (WeightType) == 0 ) Weight[Multiplier] = 1 + ( Coefficient *
Multiplier );
  if ( (WeightType) == 1 ) Weight[Multiplier] = ( 1 + Coefficient )
^Multiplier;
  TotalWeights = TotalWeights + Weight[Multiplier];
```

```
if ( Multiplier == Period ) TotalWeightsWithoutHistory =
TotalWeights - Weight[Multiplier]; }
```

Find the Start Position and Calculate First CMAs Without Historical Data

```
CoefficientMovingAverage[0] = 0;
for ( i = 0; i <= BarCount -1; i++ ) if ( AveragedData[i] > 0 OR
AveragedData[i] < 0) { StartPosition = i; break; }
for ( BarPosition = StartPosition + Period -1; BarPosition <=
StartPosition + ( 2* ( Period -1 ) ); BarPosition++)
 { CummulativeWeightedData = 0; Counter = 0;
  for ( AveragedBars = 1- Period; AveragedBars <= 0;
AveragedBars++)
   { CummulativeWeightedData = CummulativeWeightedData + (
AveragedData[BarPosition+AveragedBars] * Weight[Counter] );
Counter++; }
  CoefficientMovingAverage[BarPosition] =
CummulativeWeightedData / TotalWeightsWithoutHistory; }
```

Calculate the Following CMAs With Historical Data

```
for ( BarPosition = StartPosition + ( 2* Period ) -1; BarPosition <=
BarCount -1; BarPosition++)
 { CummulativeWeightedData = CoefficientMovingAverage[BarP
osition-Period]; Counter=1;
  for ( AveragedBars = 1- Period; AveragedBars <= 0;
AveragedBars++)
   { CummulativeWeightedData = CummulativeWeightedData + (
AveragedData[BarPosition+AveragedBars] * Weight[Counter] );
Counter++; }
  CoefficientMovingAverage[BarPosition] =
CummulativeWeightedData / TotalWeights; }
```

Plot CMA

```
Plot ( CoefficientMovingAverage, "CMA", ParamColor( "CMA
Color", colorCycle ), ParamStyle("CMA Style"), 0, 0, 0 );
```

Testing Results

The testing of the CMA was performed on the stocks of the S&P 100 index for three years, from January 2016 to December 2018 on the daily timeframe. The strategy used was the simplest, which was the single crossover tactic; buy when the closing price crosses the moving average upwards (Bullish crossover), and sell when the closing price crosses the moving average downwards (Bearish crossover). Also, only long positions were taken for the sake of simplicity.

The portfolio was adjusted to allow the maximum of 100 simultaneous open positions to allow open trades in all available stocks at the same time. Besides, the position size for each trade was set as 1% of the portfolio to allow equal exposure.

Different types of moving averages were tested using the closing price data, and the period of 19 days was selected (based on previous mapping for the best CMA period selection). Then, the results were clarified in Table 6.

Table 6. Testing CMA against other averages on the S&P 100

Item	CMA (0.45, Simple)	CMA (0.1, Compound)	SMA	WMA	EMA
Whole Trades					
Number of All Trades	94	92	92	129	89
Average Outcome Percentage per Trade	1.04%	0.92%	-0.06%	-0.56%	0.07%
Average Exposure Percentage	98%	98.7%	97.5%	97.6%	98.1%
Winning Trades					
Number of Winning Trades	30	29	26	32	24
Average Profit Percentage per Winning Trade	6.19%	6.4%	4.39%	3.01%	5%
Average Bars Held per Winning Trade	19.9	21.2	20.3	15.8	23
Maximum Consecutive Winning Trades	3	4	2	4	3
Losing Trades					
Number of Losing Trades	64	63	66	97	65
Average Loss Percentage per Losing Trade	-1.37%	-1.61%	-1.81%	-1.74%	-1.75%
Average Bars Held per Losing Trade	3.7	3.5	4.5	3.7	4.3
Maximum Consecutive Losing Trades	10	7	7	19	11
System Return & Risk					
Compounded Annual Return	32.57%	26.43%	-3.61%	-23.15%	-0.74%
Maximum Trade Percentage Drawdown	-7.9%	-7.9%	-8.1%	-14.8%	-11.4%
Maximum System Percentage Drawdown	-16%	-23.9%	-28.2%	-56.8%	-26.5%
Ulcer Risk Index	5.73	8.59	8.57	31.35	9.4

Item	CMA (0.45, Simple)	CMA (0.1, Compound)	SMA	WMA	EMA
System Risk/Reward Ratios					
Profit Factor	1.89	1.62	0.91	0.55	0.98
Payoff Ratio	4.02	3.52	2.32	1.66	2.66
Probability of Winning Trade	31.9%	31.5%	28.3%	24.8%	27%
Compounded Annual Return / Maximum System Percentage Drawdown	2.03	1.11	-0.13	-0.41	-0.03
Ulcer Performance Index	4.81	2.49	-1.01	-0.9	-0.61
K-Ratio	0.12	0.09	0.02	-0.04	0.04

Discussion

CMA Combined With Time Analysis

The technical analyst identifies an active cycle in the prices when a three or more successive waves (move and its correction) take nearly the same duration. Therefore, it is mandatory to adjust the period of the moving average equal to this cycle duration. However, many times, the simple moving average (before backward shifting) lies far below some price bottoms, and some other price bottoms false break this moving average. Moreover, it is common that the channels around the centered moving average can barely contain the price peaks and bottoms accurately without false breaks or being far from price turning points.

An ultimate solution is to use the CMA that is not only committed to the period and averages only the prices through the wave duration. But also, the CMA coefficient has a wide range to be fine-tuned, allowing the CMA line to convincingly touch the price bottoms (before backward shifting), and leading the channels to accurately hug the price turning points (after centering the CMA). Therefore, the CMA opens the limits for the time analysts to enhance their use of channels in time cycles.

Coefficient adjustment enhance Risk-adjusted Return:

In the past, we were blocked to use only the unweighted SMA or the overweighted WMA, but the CMA opens the wide range of weighting system between both of them. To know whether that adjustable coefficient is beneficial, we studied the CMA over the constituents of the S&P 100 by the single crossover tactic for three years starting from 2016 until 2018.

Ulcer Risk Index = Square root of [Sum of Squared System Percentage Drawdowns / Number of Bars]

Unlike the standard deviation, the ulcer risk index measures only the downward volatility, and from the previous peak rather than from the mean. Therefore, it represents how much the system can maintain achieved returns, by less in number and shallow (depth of drawdown) and rapidly recoverable drawdowns (duration of drawdown).

Ulcer Performance Index (UPI) or Martin ratio = [Total Return - Risk Free Return] / Ulcer Risk Index

UPI measures the risk-adjusted return of the equity curve of the trading strategy.

Figure 4. UPI of CMA with different periods and coefficients on the S&P 100

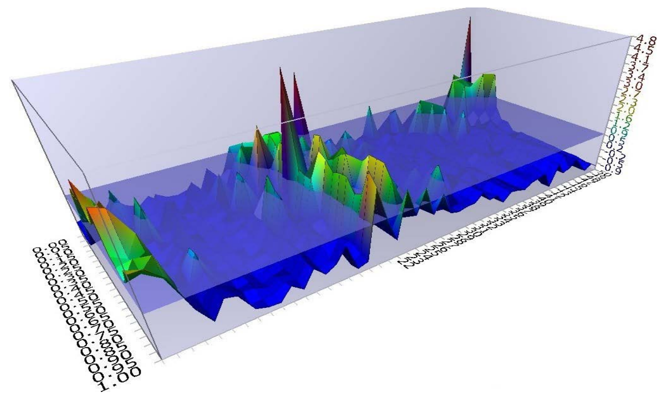


Figure 4 represents a 3D chart where the X-axis shows the different periods of the CMA ranging from 2 to 50; the Y-axis shows the different coefficients of the CMA ranging from 0 to 1 (with intervals of 0.05); the Z-axis shows the Ulcer Performance Index (with a water level at 0.5 to facilitate visual analysis). This chart proves the following:

1. Some CMAs, with coefficients between zero and one, have UPI not only higher than the UPI of the CMA with the same period and coefficient zero (that resemble the SMA with considering the history), but also higher than the UPI of the CMA with the same period and coefficient one (that resemble the WMA considering the history).
2. This situation is not a single spike in the chart but a chain of mountains as occurring in the periods from 17 to 27 with nearly all the coefficients between zero and one. This proves that it is not an exceptional case found by a wicked data mining, but it is the fact that we were in a bad need to open the field of weighting systems to enhance the moving average strategies.

Conclusion

- The EMA has a lot of statistical and logical pitfalls that make its use questionable and should be revised.
- The averages used in the equations of many technical indicators are logically to be arithmetic average, but SMA is usually avoided because it can give zero value that ruins the equation if the average value is in the denominator of a division. However, it is advised that the CMA with a coefficient zero replace all these averages, as it resembles the SMA but with the advantage of containing the historical data, so it can rarely give a zero value.
- The averages used as a technical tool in a trading strategy are advised to be the logical WMA, as it has a statistical concept in averaging, with the advantage of weighting the recent data. However, it is advised that the CMA with a coefficient one replace all these averages, as it resembles the WMA but with the advantage of containing the historical data, and it can give better results.
- CMA with the adjustable coefficient between zero and one allows the user to apply his own suitable tested weights; also the compound coefficient introduces a new edge in the weighting system.
- CMA with the adjustable coefficient allows better time analysis using channels around the centered moving average.

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Kaufman, Perry, *Trading Systems and Methods.* 5th ed. John Wiley & Sons, 2013.

Kirkpatrick, Charles D., and Julie A. Dahlquist. *Technical Analysis: The Complete Resource for Financial Market Technicians.* 3rd ed., FT Press, 2016.

Software and Data

Testing was performed by AmiBroker software, version 6.2.1.

Data were provided by Thomson Reuters data feed.

The Ripples Effect: A Clearer View for Market Action and Price Patterns

By Mohamed Ashraf Mahfouz, CETA, CFTe, MFTA

Mohamed Ashraf Mahfouz, CETA, CFTe, MFTA

c/o Commercial International Brokerage Company (CIBC)
West Tower, Galleria 40,
26 of July axis extension Sheikh Zayed,
6 of October City, Egypt

+2 01001842420
mohamed.ashraf@cicapital.com

Introduction

How do markets move? It is question that is asked by everyone, but unfortunately it has no clear or confident answer. For example, a fundamentalist would say that markets move randomly around its intrinsic value, without denying the trending manner the markets move in. A technical analyst or chartist would say that markets move in trends, surely without denying the existence of randomness, or doubtful areas, and the continuous false breaks the markets witness during these trends. Can it be inferred, then, that markets move in clear trends, but in a random way? This article tries to answer this question by discussing the causes for market movements. It tries to analyze how to identify the general market trend and expect the random movements that constitute it using a simple logical tool. The article draws heavily on the work of Brian J. Millard (1999) on channels.

Price Movement: Questioning the Demand and Supply Equation

When it comes to market action it is always seen as a result of the demand and supply equation or bulls versus bears. If bulls are stronger than bears the trend is believed to be up and consists of continuous higher lows and higher highs. On the other hand, if bears are stronger than bulls the trend is then considered down and consists of continuous lower highs and lower lows. Sometimes if volume is available we can use it to confirm those directions or breakouts.

Based on the previous logic, price patterns are defined as graphical formations that appear on the price chart, have predictive value, and are created by demand and supply forces. Accordingly, if we have, for example, a horizontal resistance level and a higher low pattern, we identify it as a bullish ascending triangle, and the next direction bias will be to the upside. On the other hand, if we identify a head and shoulders pattern thatconsists of same lows between three peaks, but the third peak is a lower high (after a higher high), the next direction biasedness will be to the downside etc.

The following charts of Ezz Steel Company (ESRS.CA) in the Egyptian Stock Market are showing the above-mentioned situation as follows:

Chart 1. Ezz Steel Company (ESRS.CA) weekly candlestick chart with volume

As can be seen in Chart 1, the stock was in a downtrend from Q4 2014 until Q3 2016, forming consecutive lower highs and lower lows and showing that bears were in control. In Q4 2016, the stock achieved a clear higher low formation as it did not make a new low and started to rise steeply, breaking the previous peak to the upside and was accompanied with high volume. At this point, this kind of breakout indicates that bulls are in control and the next direction is going to be to the upside. That is exactly what happened afterwards, as shown in Chart 2.

Chart 2. Ezz Steel Company (ESRS.CA) weekly candlestick chart with volume (update)

But does it always work like this?

The previous example proves that the market direction is indicated by the supply and demand forces represented by peaks and bottoms. Unfortunately, this is not totally true, as there are lots of other examples that show the same situation, but the end result or direction is different. See the following examples.

Example 1:

Chart 3. Qalaa Holding Company (CCAP.CA) weekly candlestick chart with volume

As can be seen in the Chart 3, the stock was in a downtrend from Q4 2009 until Q2 2012, forming consecutive lower highs and lower lows, showing that bears were in control. In the Q3 2012, the stock achieved a clear same low formation, as it did not make a new low and started to rise, breaking the previous peak to the upside and was accompanied with high volume forming a double bottom formation. At this point, this kind of breakout indicates that bulls are in control and the next direction is going to be to the upside. But this time, that did not happen, and the stock, after a minor rise, started to decline, as shown in the Chart 4.

Chart 4. Qalaa Holding Company (CCAP.CA) weekly candlestick chart with volume (update)

Thus, a new high breakout in this case is considered misleading, and the stock went down. From demand and supply perspective, this case does not make any sense; to break a resistance with high volumes and the stock still goes down is very weird and questions the whole theory of demand and supply.

The following are examples of two indices of the Egyptian Stock Market and the U.S. market.

Example 2:

Chart 5. The Egyptian Stock Market index (.EGX30) daily candlestick chart

Chart 5 displays the EGX30 daily chart; it shows three different directions—two downtrends and one uptrend. There are three circles on the chart that highlight the break of resistance levels to the upside after a higher low formation. This situation should always indicate a trend reversal, or at least a bullish scenario. Despite those upside breakouts, only one of them resulted to the upside, and the other two resulted to the downside. Such situations are referred to as failed breakouts, whipsaws, or bull traps because, according to the demand and supply analysis, simply nothing can justify that an upside breakout will result in a downward direction.

Example 3:

Chart 6. The Dow Jones Industrial Average (.DJI) weekly candlestick chart

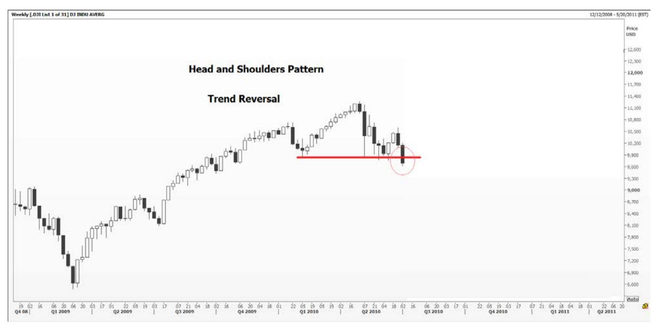


Chart 7. The Dow Jones Industrial Average (.DJI) weekly candlestick chart (update)

Charts 6 and 7 demonstrate the Dow Jones Industrial Average (.DJI) in year 2010. The index has achieved a clear head and shoulders pattern on the weekly chart during the first half of 2010, with a clear breakout to the downside.

As can be seen in Chart 7, despite this clear downside breakout, the end result was to the upside, and the index went to new highs as if nothing happened in the first half of 2010; the only commentary or justification will be that the pattern failed.

There are many examples that show bearish patterns or signals that resulted in bull trends or positive direction and bullish patterns or signals that resulted in bear trends or negative direction. Thus, the market action should be looked at from a different perspective besides demand and supply (bottoms and peaks).

Controversy Over Market Movements

The main reason why the market it is looked at in terms of demand and supply is that people want to justify the force behind the market upside and downside movements. But if the main forces are demand and supply, then the economic theory would imply that markets are moving around an equilibrium point (demand=supply). So if the demand is bigger than the supply, the price will increase, then the quantity of supply will start to increase, and hence, the market will start to decline until it reaches the equilibrium point. On the other hand, if the supply is bigger than the demand, the price will decrease, then the quantity of demand will increase, and hence, the market will start to rise until it reaches the equilibrium point. This idea is very similar to the fundamental analysis explanation to the price action, as it suggests that markets are moving randomly around their intrinsic fair values. Thus, if this justification is completely right, markets won't have any trend; they will always move in sideways. But practically speaking, this situation cannot be true at all; we have seen markets that have been in a trend for years, either to the upside or to the downside. That is why one of the main Dow Theory tenets says that "A trend is assumed to be in effect until it gives definite signals that it has reversed."

Main Idea

The main reason why markets move in trends in a zigzag way is that it is composed of more than one demand and supply equation, or in other words the market consists of more than one TIME Span direction that act together at the same point of time.

Dow Theory states that, "The Market has three trends". Dow considered a trend to have three parts; primary, secondary and minor which he compared to the tide, waves and ripples of the sea. This explanation is very true about how the market really acts. It should be emphasized however that these three parts should not be considered as three different stages. We believe that the three trends are acting together at the same time all the time. Thus, instead of dividing the trend into bulls and bears or long-term versus medium-term trends one should divide it into long, medium, and short-term investors acting inside the market at the same time. This was explained by the time cycle analysis in the sense that the trend consists of all active cycles or what is referred to as the summation principle.

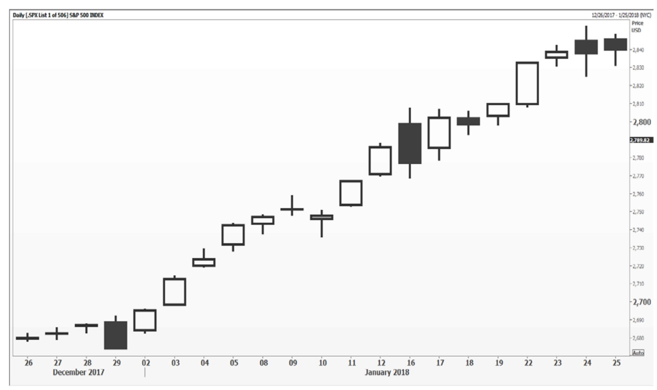
We believe that the main drive for investment is time before the amplitude. To clear this point up, let us assume that we have a day trader who entered a trade by buying a stock at a specific level. If the stock rose during the session, this trader will sell to take profits, but what if the time passed and the stock did not rise? The trader will still sell it even if he realized a loss because he is a day trader (time). The same characteristics of the day trader are applied on the short-term investors that invest during three weeks or one month duration and are also applied on the medium- or long-term investors that invest in the market every year or three to five years or more.

The following examples will show six different situations of how investors with different time spans act together to create the market trend using the S&P 500 index daily price chart.

Example 1:

When nearly all types of investors are acting positively inside the market.

Chart 8. The S&P 500 index (.SPX) daily candlestick chart

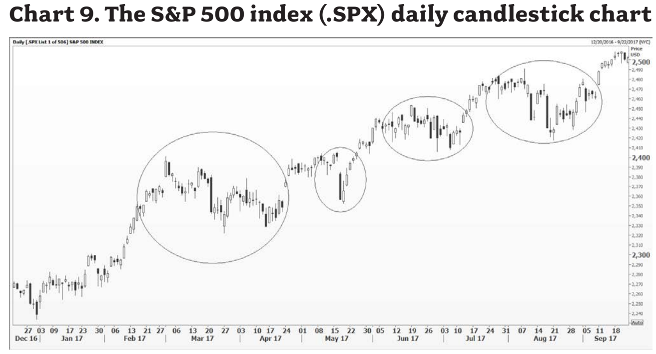


As can be seen from Chart 8, the market rose almost every day continuously except for a few situations where day traders affected the close of some sessions, but they do not interrupt the direction.

Example 2:

When medium- and long-term investors are acting positively inside the market but short-term investors are acting negatively.

Chart 9. The S&P 500 index (.SPX) daily candlestick chart

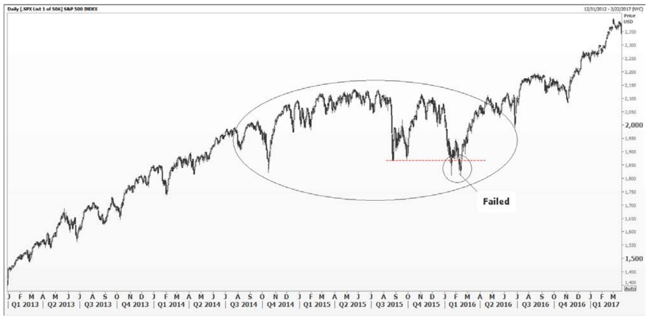


By looking at the chart above, it is very obvious how the short-term investors' negative attitude affected the market direction in some situations. Eventually, the end result is that the market will continue to go up as the medium- and long-term investors are still positive. That is why the market will witness lots of negative sell signals, but it will resume to the upside, and if there is a bearish pattern appeared it will fail.

Example 3:

When long-term investors are acting positively inside the market but medium- and short-term investors are acting negatively.

Chart 10: The S&P 500 index (.SPX) daily candlestick chart



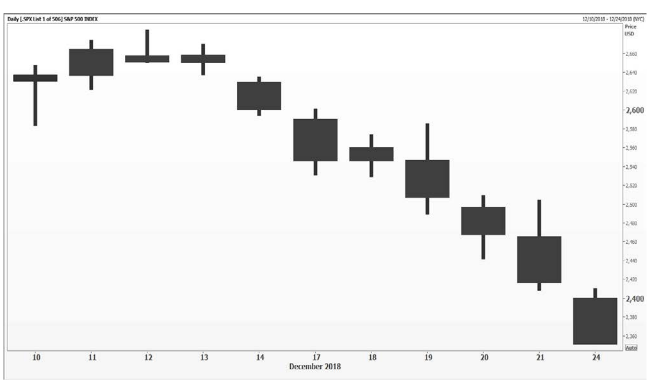
It can be shown from the above chart how the market trend can be interrupted for a whole year (Year 2015—inside the circle). Despite the medium- and short-term selling pressure, the overall trend direction did not shift from up to down, but it nearly moved sideways, and any downside breakouts failed to put the market lower because the long-term investors were buying the market.

This point is extremely important, and it must be clear that the next potential direction of any breakout of a support/resistance or price pattern boundary is not based on its shape or name but on the direction of the longer term trend. Thus, it is not based on demand and supply situation; it is based on the direction of the different time span trends, and thus, the bigger time span trend will identify the next direction.

Example 4:

When nearly all types of investors are acting negatively inside the market.

Chart 11. The S&P 500 index (.SPX) daily candlestick chart

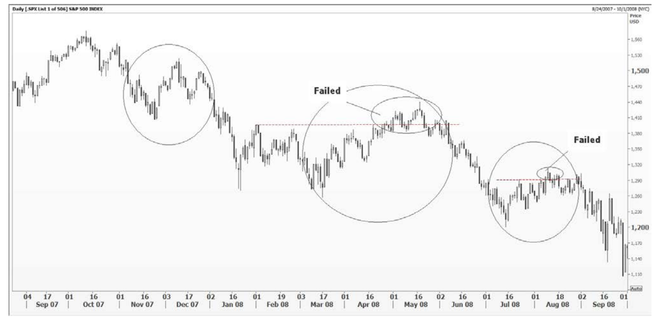


As can be seen from Chart 11, the market lost nearly 20 percent of its value in a continuous direction without any interruption during December 2018.

Example 5:

When medium- and long-term investors are acting negatively inside the market but short-term investors are acting positively.

Chart 12: The S&P 500 index (.SPX) daily candlestick chart

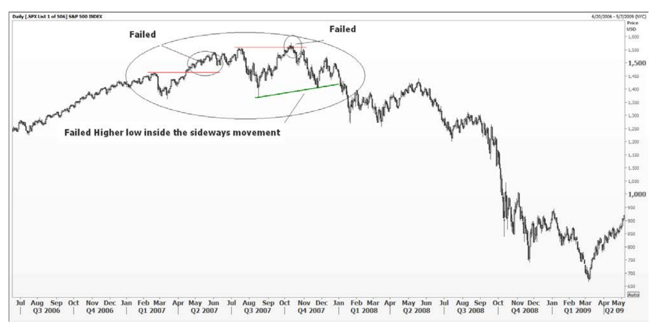


It is very obvious from looking at Chart 12 how the short-term investors' positive attitude affected the market direction in some situations. Eventually, the end result is that the market continued to go down as the medium- and long-term investors are still bearish. That is why the market will witness lots of positive buy signals, but it will resume to the downside, and if a bullish pattern or upside breakout appears, it will fail.

Example 6:

When long-term investors are acting negatively inside the market but medium- and short-term investors are acting positively.

Chart 13. The S&P 500 index (.SPX) daily candlestick chart



In 2017, the market was moving in a high volatility sideways that contained more than a higher low formation and upside breakouts, but they all failed to continue the upside movements. Despite the medium- and short-term buying power, the overall trend direction did not continue to the upside but rather shifted from up to down after a medium-term sideways struggle that ended to the downside with the power of the long-term investors that were selling the market. Thus, the bigger time span identified the next direction.

Price Ripples

By examining the previous six examples, we will figure out that the more all types of investors are in harmony taking the same direction, the less fluctuation the market will witness. On the other hand, less harmony between different types of investors leads to more fluctuation in the market. This fluctuation is created when two or more types of investors are moving against each other, which can be called price ripples or price patterns.

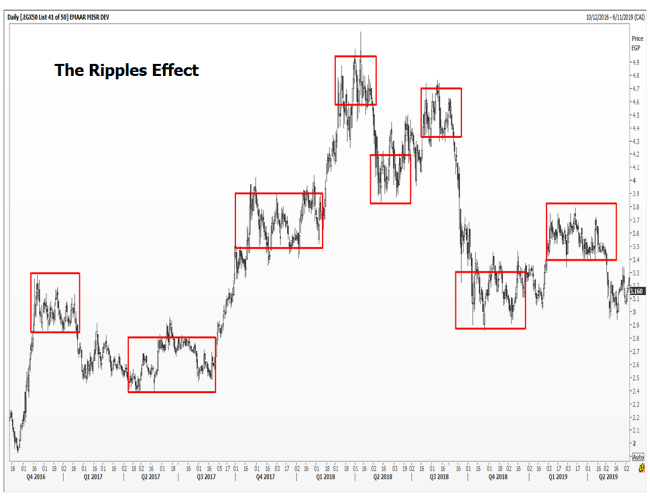
Price patterns can now have a new definition: *price ripples that are created because of the collision of two or more different trends (different in time and direction), the following direction of any price pattern is based on the direction of the longer term trend, not on the structure or shape of the pattern.*

Price patterns are similar to the water ripples that are created when two or more water flows are moving against each other, as shown in Figure 1.

Figure 1. Water ripples created as a result of the collision of different direction water waves

Chart 14 shows how the Ripples Effect appears on a real price chart when two or more types of investors (in direction and time) collide.

Chart 14. Emaar Misr for development of daily candlestick chart



How are these ripples created? This question will be answered in the following section that explains how the trend is composed and how different time span trends affect each other.

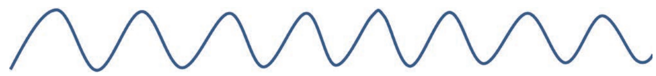
Identifying the Trend Composition

To try to understand how the trend moves when all types of trends work together, it will be easier to illustrate first how each trend hypothetically works alone and then how the trend of a higher time span will affect the trend of a smaller time span.

Hypothetical Illustration of the Effect of a High Time Span Trend on the Smaller One

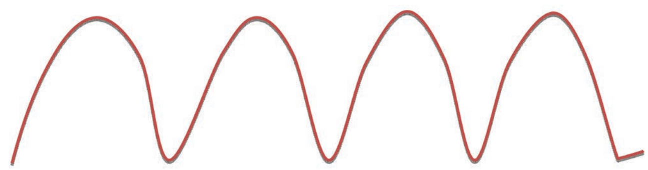
First, let us assume that we have only short-term investors in the market who buy the market on short-term equal intervals of time. The expected end result is that the market will move in sideways movement with a relatively small magnitude. It will take the following shape:

Figure 2. Market movement when there are only short-term investors



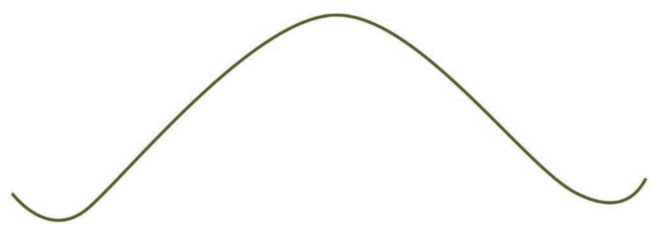
Now let us assume that we have only medium-term investors in the market who buy the market on medium-term equal intervals of time, which is surely longer than that of the short-term investors. The expected end result is that the market will move in sideways movement but this time with relatively bigger magnitude than that of the short-term investors. It will take the following shape:

Figure 3. Market movement when there are only medium-term investors



Finally, assuming only the existence of long-term investors:

Figure 4. Market movement when there are only long-term investors

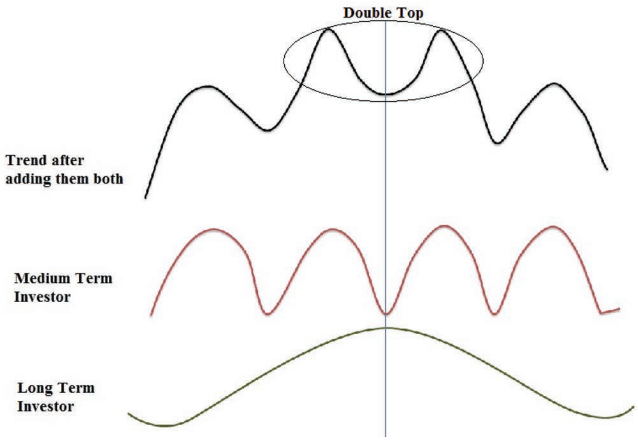


If we hypothetically look at the long-term investors at the same period of time that we examined the medium and short-term investors, it will nearly create only one rise and one fall.

The previous three figures showed the hypothetical shape of the market when we separate each type of investor; we can clearly see that the end result of each is that the market will move sideways, and the only difference is that the time between bottoms will differ and of course the magnitude of every rise will differ. Longer term investors will have greater magnitude and more time elapsed between each successive bottom. This is what is referred to as "proportionality principle" in Time Cycles Theory.

After imagining how the market will move if it only includes one type of investors, Figure 5 will show how the trend will differ when we add more than one type of investor to the other or what is referred to as the "summation" principle in Time Cycles Theory.

Figure 5. Adding the long-term investor to the medium-term investor



As can be seen in Figure 5, we can divide it into three stages:

The first stage: The medium-term investor was affected by the left side or the rising side of the long-term investor, so whenever the medium-term investor is declining or pushing the market lower, it will not reach the previous low like when it was alone and will make a higher low, and when it rises, it will make a new high, not the same high as when it was alone.

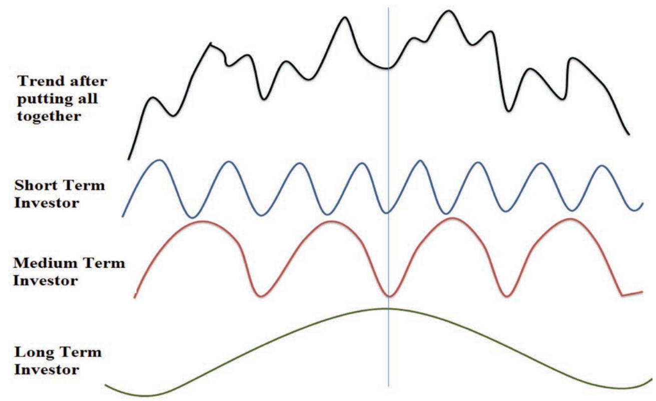
The second stage: This stage is very important when the long-term investor starts to reverse from up to down (from left side to right side) and the medium-term investor is still involved and going upward. This situation creates what we defined as price patterns or price ripples. In the above situation, the medium-term investor nearly took the shape of the sideways as if it is alone. We can identify this sideways as a "double top" pattern. What makes us claim that it is a double top formation not a rectangle formation, or that in such case, the end result will be to the downside, is that the long-term investor will turn to the negative side, and the market won't be able to break to the upside. Thus, the pattern is created by the intersection of both investors (long-term and medium-term), but what identifies the next direction is the long-term investor.

The third stage: The medium-term investor was affected by the right side or the falling side of the long-term investor, so whenever the medium-term investor is rising or pushing the market higher, it will not reach the previous high like when it was alone; it will make a lower high, and when it falls, it will make a new low, not same low as when it was alone.

By realizing the idea of those three stages, we can easily identify the direction of the investor of a longer time interval by looking at the peaks and bottoms of the investor of a shorter time interval. If, for example, the medium-term investor is making a higher low, that means that the longer term investor is still looking upward, preventing the medium-term investor to reach its previous low, and thus, we should be biased for a new high. And if the medium-term investor is getting weaker and is not able to make a new high, that means that the longer term investor is reversing. Lastly, if the medium-term investor is making a lower high and lower low, that definitely means that the longer term investor is declining.

This idea is very important to understand before going forward with our article because we will rely on it after we identify the different types of investors in real prices in order to expect the next market movement. Figure 6 includes all types of investors together and how the trend will be created.

Figure 6. Putting all types of investors together



Identifying Different Types of Investors in Price Charts

The big challenge is to isolate different types of investors as we did previously, but this time on price charts. This can be done using the "moving average envelopes" or the "percentage envelopes" or the "envelopes" indicator and without the use of time cycle analysis.

The envelopes are fixed bands that surround the moving average by a certain fixed percentage. It is originally made for the sake of filtration for the price crossover with the moving average during trending phases, and also made for trading during sideways by widening the bands in order to trade between its boundaries.

In this article, we use the envelopes in a different way in order to isolate the different types of investors by enveloping the price action of each investor separately. First, let us establish the main rules when we apply envelopes.

1. **Use the daily price chart only.** All types of investors will be identified from the same chart, including the long-term investors. The chart that will be used is always the shortest term chart in our analysis, which is the daily chart.
   For forex markets, we will use the hourly chart or the half-hour chart as our main chart.
2. **Use centered moving average envelopes.** It is already known that envelopes are typically moving averages that are shifted to the upside and to the downside. However they are averages for the price, but they are plotted at the last traded price. They should, however, be plotted in the mid-point of the range under study. For example if we are using 10-day envelopes, every new point should be plotted on the fifth day not on the 10th day. In this way, the cycle for each type of investor will be displayed in clearest way.
3. **Start drawing your envelopes from the small investor to the longer term investor.** Thus, we will draw from the inside to the outside. Usually we draw three channels of envelopes that represent the short-term, medium-term, and long-term investors. But you can use a longer term channel for secular degree trends.

The last general guideline is that you can use time analysis and price oscillators (Stochastic Slow Oscillator) to help you choose the right span of the centered envelopes.

The following section will present a case study by applying envelopes on real stock prices in order to identify different types of investors in the same price chart.

Case Study: Emaar Misr for Development (EMFD.CA) in the Egyptian stock market

Charts 15 and 16 are daily price charts for Emaar Misr for Development, which is a stock in the Egyptian stock market. This chart was chosen as it nearly includes the three types of trends (Up — Sideways — Down).

Chart 15. Emaar Misr for development of daily candlestick chart (Price Only)

Chart 16. Emaar Misr for development of daily candlestick chart (with annotations)

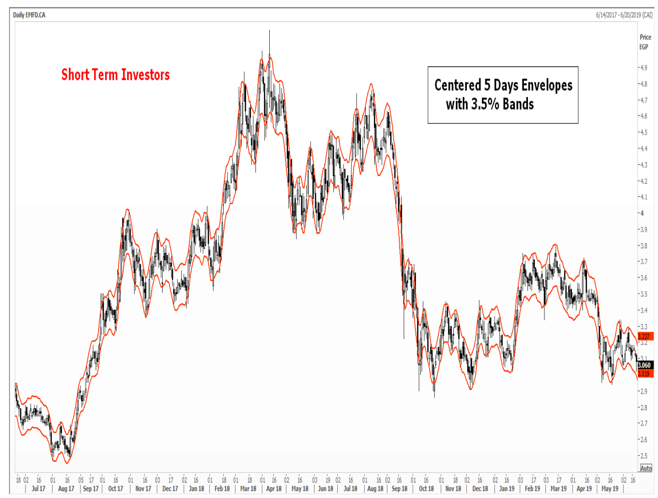
Looking at Chart 16, we can clearly see a lot of false breaks in different situations and directions. We can see how many times the stock broke a support to the downside but rose afterwards, and how it broke resistance to the upside but declined afterwards. We can also see on the left side of Chart 16 a symmetrical triangle formation that was broken to the downside and should have acted as reversal, but it was a false break or a failure, and the stock continued to move upward. These situations happened in many cases and nearly in all timeframes, especially in the small timeframes like daily, four hours, hourly, and 30 minute charts.

To solve this problem and try to avoid such false breaks, we have to examine the different types of investors in order to be able to predict the future direction of the stock based on the direction of each type of investor separately.

Step 1: Short-term investors

As we have mentioned before in the general rules, that will draw our envelopes from the inside to the outside. First, we will choose the envelopes that encompass price randomness. After choosing the right period and percentage of the envelopes to encompass the short-term investors' fluctuation, remember to center the envelopes in order to move identically with price fluctuations.

Chart 17: Emaar Misr for development of daily candlestick chart with centered five-day envelopes with 3.5% bands



In Chart 17, we can identify clearly repetitive bottoms and peaks that are nearly equal or near in time, which shows the short-term investors' attitude or fluctuations. We can also notice that despite the equally repetitive attitude of the short-term investors, the trend was not sideways. Sometimes it resulted in consecutive higher lows and higher highs, other times to the downside, and other times sideways. That is simply because this trend is not created just by the short-term investors; there are longer time span investors that affected the trend. This makes us move to the next step of our envelope analysis.

Step 2: Medium-term investors

To identify the medium-term investors, we will choose the right envelopes that encompass peaks and bottoms of the smaller channel of the short-term investors. We will try as much as we can to make the lower band touch most of the bottoms and the upper band touch most of the peaks of the short-term investors (smaller channel).

Chart 18. Emaar Misr for development of daily candlestick chart with centered 5-day envelopes with 3.5% bands and centered 30-day envelopes with 7.5% bands

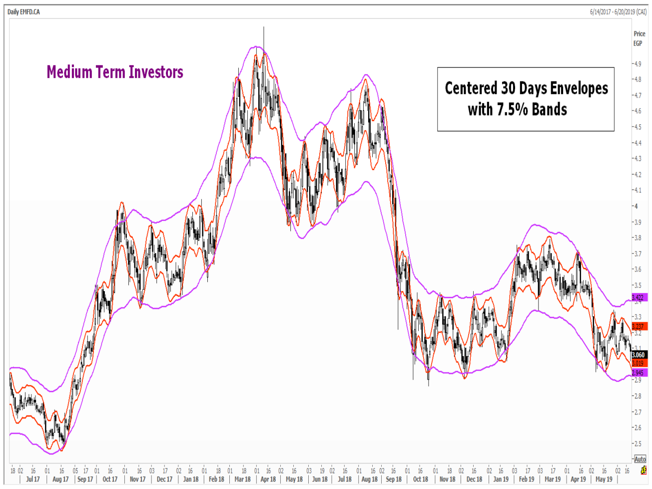


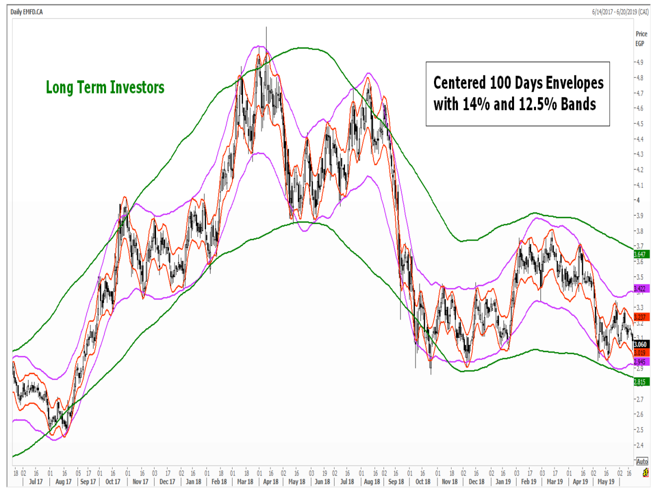
Chart 18 shows both short-term investors (red channel) and the medium-term investors (purple channel). The short-term investors on the left side of the chart consist of consecutive higher lows and higher highs because there were longer term investors that were pushing the market higher. On the other hand, the short-term investors were making lower highs and lower lows on the right side of the chart because there were longer term investors that were pushing the market lower. In cases where the short-term investors moved sideways, those were the periods where the medium-term investors were creating a bottom or a peak within the trend.

In Chart 18, the medium-term investor peaks and bottoms are now clear. We can also notice that despite the equally repetitive attitude of the medium-term investors, the trend was not sideways. The left side of the chart above consists of consecutive higher lows and higher highs, and the right side consists of consecutive lower highs and lower lows. That is simply because this trend is not created only by the short-term and medium-term investors but there are longer term investors that also contributed in this trend. This makes us move to the last step of our envelope analysis.

Step 3: Long-term investors

In order to identify the long-term investors, we will choose the right envelopes that encompass peaks and bottoms of its smaller channel of the medium-term investors. We will try as much as we can to make the lower band touch most of the bottoms and the upper band touch most of the peaks of the medium-term investors (relatively smaller channel).

Chart 19. Emaar Misr for development of daily candlestick chart with centered 5-day envelopes with 3.5% bands, centered 30-day envelopes with 7.5% bands, and centered 100-day envelopes with 14% and 12.5% bands

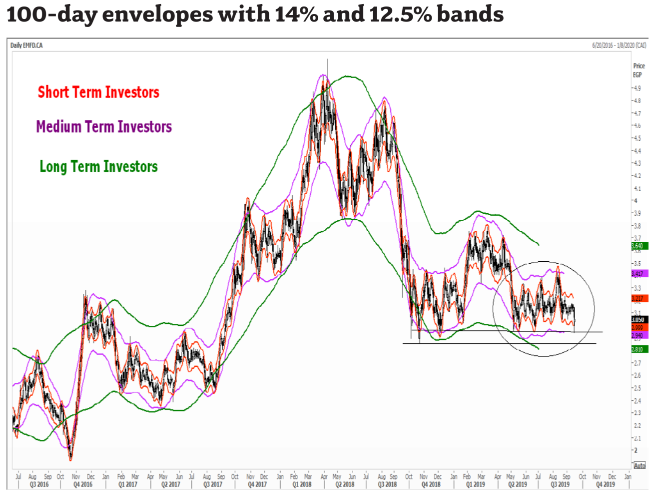


After plotting the long-term channel, we can now understand the reason behind nearly every move within the trend. We can always justify the current move or direction of the trend understudy by understanding the direction of the longer term trend or investor. For example, on the left side of the chart, since the biggest channel is moving upward, we can realize why every downside trigger failed and why, despite the violation of the lower boundary of the symmetrical triangle—which we referred to in chart 16—it did not continue to the downside and end to the upside.

In the top of this chart, we can now understand that the double-top formation was created because there were two waves moving against each other; the long-term investors were reversing from up to down, and the medium-term investors were trying to move upward again, which caused the ripples. Since the long-term investors were the party that is reversing to the downside, that meant for sure that this double-top formation will not fail and will result to the downside.

Let us look again at the same chart after updating the last price.

Chart 20. Emaar Misr for development of daily candlestick chart with centered 5-day envelopes with 3.5% bands, centered 30-day envelopes with 7.5% bands, and centered 100-day envelopes with 14% and 12.5% bands



By examining the chart above and by looking at the recent price action, ignoring the channels we drew, we will see that the stock is moving above a strong support and is not violated to the downside, as can be clearly seen in the drawn circle. Also, if we try to focus on the short-term price action inside the circle, we can see that the price did not break the support and also, there are minor upside breakouts within this sideways range. This strong support condition that also corresponds to the major broken peak on the left side of the chart and the mentioned minor upside breakouts could make us biased that the end result of this situation will be to the upside, or at least to continue sideways until we have more confirmation on the next direction. But as we explained earlier, whatever the situation and whatever the breakout direction, to anticipate the next market movement, we have to look at the trend or the long-term investor; thus, the current sideways movement (price ripples) is created because of the collision of more than one wave at the same time, and by looking at the long-term channel (green channel), we can clearly see that it is still looking downward, which means that the end result of the price ripples in the circle will be to the downside, and that the strong support will be violated to the downside. Please take a look at the update of Chart 20 below in Chart 21.

Chart 21. Emaar Misr for development of daily candlestick chart with centered 5-day envelopes with 3.5% bands, centered 30-day envelopes with 7.5% bands, and centered 100-day envelopes with 14% and 12.5% bands (updated prices)

As can be seen in Chart 21, the stock breached this strong support to the downside as expected because of the effect of the long-term investors that were looking downward.

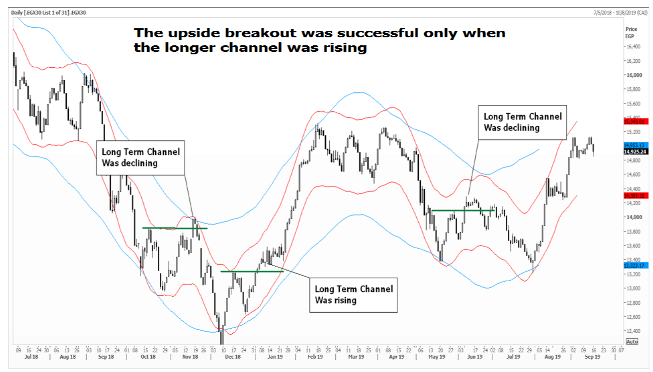
Case Study 2

In this quick practice, Chart 5 of the Egyptian stock market index EGX30 (shown below) is revisited to explain why, although there were three upside breakouts, only one of them succeeded and the other two turned negative.

Chart 5. The Egyptian Stock Market index (.EGX30) daily candlestick chart

We are going to apply the envelopes on the chart by drawing two different time span channels to see what we get.

Chart 22. The Egyptian Stock Market index (.EGX30) daily candlestick chart with centered 17-day envelopes with 3.5% bands and centered 55-day envelopes with 6% bands



In Chart 22, we can easily anticipate which upside breakout will be successful when we examine the direction of the longer term channel, when the longer term channel is rising; this is the situation when any upside breakout will succeed, as it is moving within the flow of the longer term wave.

Tools and Guidelines That Can Enhance Envelopes Analysis

Like any tool, using envelopes in that manner has some shortfalls. The main problem is that since envelopes are centered moving averages, it will always lag the price action by the amount of centralization. Thus, it is recommended to use some guidelines while using it or to use another tool besides using it to overcome this drawback.

Envelopes direction can be identified from the envelopes of shorter time span

A very important rule is that markets take time to reverse their direction. In other words, envelopes will take time to reverse from up to down or from down to up.

Thus, if we have envelopes that are looking downward and the envelopes of shorter time span are moving upward—meaning two waves are moving against each other—we have to expect that the smaller wave is the one that will be forced to look downward again because of the wave of longer time span.

On the other hand, if the smaller wave started to go down but it is not able to make a new low (higher low) then this definitely means that the envelopes of longer time span will move at least sideways and could be reversing upward. This can be shown from the example below.

Chart 23. Emaar Misr for development of daily candlestick chart with centered 30-day envelopes with 7.5% bands and centered 100-day envelopes with 14% and 12.5% bands

In Chart 23, along with two envelopes that represent two different investors, looking at the red and green arrows, it shows us the collision of the two waves. Whenever the shorter term investors touch one of the boundaries of the longer term investors, ripples are created, and the short-term movement shifts its direction.

At **Point 2,** the smaller investors were looking down, creating lower highs. But since the bigger investors were still looking upward, the smaller channel was forced to look upward again by the strength of the bigger channel.

At **Point 1,** we can see how the smaller channel created a higher low, as shown by the green arrows which makes us understand, even if the bigger channel is lagging behind, that it is reversing its direction from down to up and hence preventing the smaller channel from creating a new low. Thus, we should expect that the smaller channel will eventually make a new high.

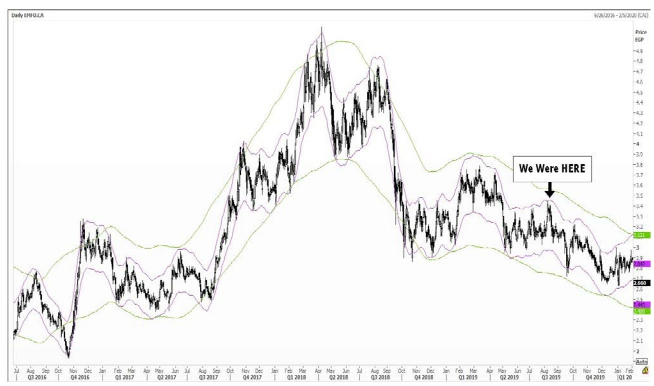
At **Point 3,** we can see how the smaller channel created a lower high, as shown by the red arrows, which makes us understand, even if the bigger channel is lagging behind, that it is reversing its direction from up to down and hence preventing the smaller channel from creating a new high. Thus, we should expect that the smaller channel will eventually make a new low.

At **Point 4,** this is a good practice to understand how we can expect the next market movement despite the delay of the channels because of the centralization. As we can see inside the smaller channel, the prices were moving sideways biased to up, which gave us the feeling that the market will break to the upside. But by looking at the lagging bigger channel, it is still looking downward; thus, we can imagine that if we extend its boundaries, it will hit the smaller channel at some point to either push it to a new low or at least a higher low. Thus, we should expect that the stock will go down because of the direction of the bigger channel. Chart 24 is the same as Chart 23 but includes an imaginary extension for the channels and our expectation.

Chart 24 Emaar Misr for development of daily candlestick chart with centered 30-day envelopes with 7.5% bands and centered 100-day envelopes with 14% and 12.5% bands (with a hypothetical expectation of the channels next direction)

Chart 25 will show the real end result of the price action.

Chart 25. Emaar Misr for development of daily candlestick chart with centered 30-day envelopes with 7.5% bands and centered 100-day envelopes with 14% and 12.5% bands (real update)

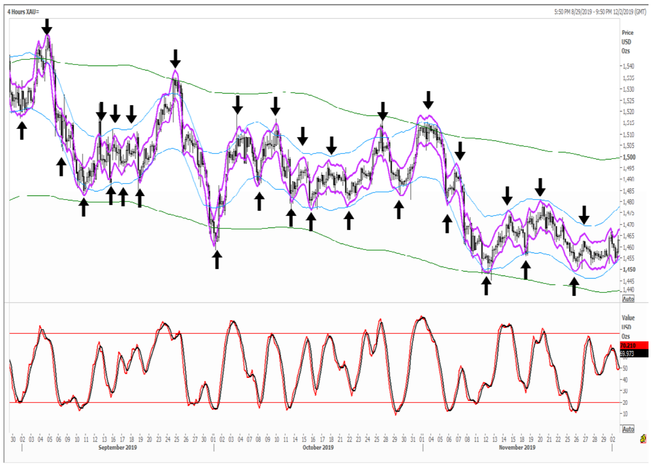


Stochastic Slow Oscillator helps in identifying turning points

After understanding the relation between the different channels, we can use the Stochastic Slow Oscillator (9,5,3) to provide the trigger of the turning points through the crossovers of %K to %D. We believe that the Stochastic Oscillator is the best tool to provide the turning point at the exact peak or bottom; thus, it will enhance your trading and solve the lagging problem of the channels.

Chart 26 will show the turning points of the smallest channel. If you want to anticipate the turning point of the bigger channels, use the bigger time span chart. So, if you are using the daily chart, use the weekly or monthly charts; if you are using hourly chart, use the 4-hour or daily or weekly chart.

Chart 26. Gold 4-hour candlestick chart with centered 4 4-hour envelopes with 0.4% bands, centered 30 4-hour envelopes with 0.8% bands, and centered 210 4-hour envelopes with 2% bands along with Stochastic Slow Oscillator (9,5,3)



As can be seen from Chart 26, all bottoms and peaks of the smallest channel (purple channel) correspond to the %K & %D crossovers.

To benefit from the Stochastic Slow Oscillator in the bigger channels, the following example will clear this point.

Chart 27. Gold 4-hour candlestick chart with centered 30 4-hour envelopes with 0.8% bands and centered 210 4-hour envelopes with 2% bands along with Stochastic Slow Oscillator (9,5,3)

In the chart above, we have excluded the smallest channel, and as you can clearly see, the Stochastic Slow Oscillator will not help to anticipate the turning points of the bigger channels.

As can be shown in the circle in the chart above, the smaller channel created a lower high formation, indicating that the bigger channel is turning from up to down, and that is why we could have expected a new low in prices, which actually happened.

We can also use the Stochastic Slow Oscillator but on the longer term charts (daily chart in this example) to help us in confirming the reversal of the bigger channel, as can be seen in Chart 28.

Chart 28. Gold daily candlestick chart along with Stochastic Slow Oscillator (9,5,3)

We can see the clear negative divergence trigger provided by the Stochastic Oscillator with the price action that anticipates and confirms the weakness we saw earlier by the channels (in the 4-hour chart).

Momentum indicator can show weakness or strength of the channels

The envelopes are centered and shifted moving averages; thus, they may be lagging and they take some time to reverse from down to up or from up to down. Calculating a four-period momentum for the envelopes itself could provide us with an early signal that the channel's momentum is slowing down in its direction and is about to reverse. The following example of the U.S. Dollar versus the Japanese Yen will illustrate this tool.

Chart 29: U.S. Dollar/Japanese Yen daily candlestick chart with centered 34-day envelopes with 1.8% bands and centered 120-day envelopes with 3% bands along with 4-day momentum of the 120-day envelopes

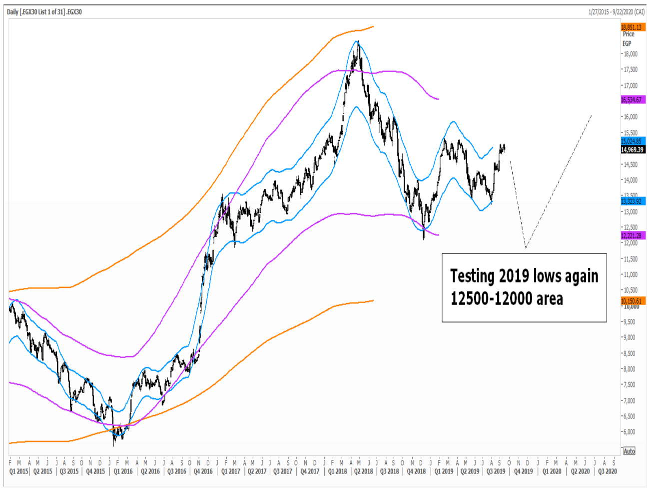
We can see from Chart 29 how nearly every turning peak or bottom of the big channel (blue channel) was preceded by a divergence with the momentum indicator (in the lower panel). It was showing the slowdown in the momentum of the rise or fall, indicating that the rising channel will reverse to the downside, and when it is falling, it indicates that it was about to reverse to the upside.

Spotlight on IFTA Conference 2019 Predictions

I had the honor to participate as a speaker at the IFTA conference that was held in Cairo in October 2019. The topic of my session was actually the topic of this article. To prove the validity of the topic, I had provided predictions on the Egyptian stock market and the U.S. equity market based on the envelopes analysis as explained. It is my pleasure to show you our prediction at that time and the update six months later.

The Egyptian Stock Market Prediction

Chart 30. The Egyptian stock market index EGX30 daily candlestick chart with centered 55-day envelopes with 6% bands and centered 180-day envelopes with 13% bands, and centered 600-day envelopes with 30% bands



In October 2019, EGX30 was almost at 15,000 points. We have explained before that we should make our analysis from inside to outside, so by looking at the smaller channel, we will find out that it was moving sideways and that the bigger channel (the purple channel) was looking downward; thus, our expectation then was that the index should test the year low again at 12,500–12,000 points and could extend to make a new low until it reaches the lower boundary of the long-term investors channel (orange channel). The following chart is an update six months later.

Chart 31. The Egyptian stock market index EGX30 daily candlestick chart with centered 55-day envelopes with 6% bands and centered 180-day envelopes with 13% bands and centered 600-day envelopes with 30% bands (six-month update)

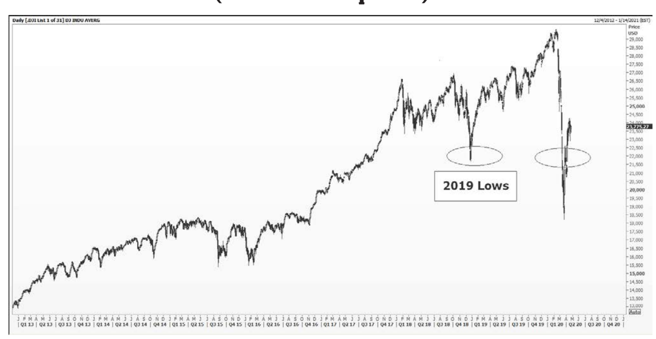
Six months later, the market actions confirmed the previous expectations. More importantly, staying above 12,000 points may not be considered as a bearish situation but high volatility sideways. Being below this area would make most of the investors look at the market as a bearish market, as it will create major lower high and lower low pattern. Yet, since the market reached the lower boundary of the long-term channel, we expect that the market will witness a significant medium- to long-term rally.

The U.S. Stock Market Prediction

Chart 32. The Dow Jones Industrial Average (DJI) daily candlestick chart with centered 50-day envelopes with 7% bands and centered 200-day envelopes with 13% bands along with 4-day momentum of the 200-day envelopes

In October 2019 the DJI was at 27,200 points. As you can see from the chart above, the Ripples Effect was created during two complete years (2018–2019), which is—as mentioned before—the result of the collision of two different investors. Also, by looking at the 4 momentum of the bigger channel (long-term investors), it is evident that the momentum of the rising long-term upward envelopes is diminishing, which made us expect that the end result of this Ripples Effect will be to the downside as the long-term channel is about to reverse. Thus, we were expecting that the Dow Jones Industrial Average is at least going to retest 2019 lows at 22,000–21,500. Chart 33, six months later, confirms that.

Chart 33. The Dow Jones Industrial Average (DJI) daily candlestick chart (six-month update)



Conclusion

Observing the Ripples Effect or the periods of price fluctuations brought us closer to understanding how the market actually works. It made us look at the market action from the relation of different time span investors' perspectives rather than looking at it from the demand and supply forces side.

Identifying the different types of investors using envelopes has the following merits:

1. Having a clearer view for the market action.
2. Understanding how the participation of different time span investors at the same time creates the market trend.
3. Having a new understanding of price patterns and understanding that it is created when two or more different types of investors (in direction and time) collide, and that is why we called them price ripples.
4. Not to rely on the price pattern shape to anticipate the next market movement but to rely on the direction of the longer term channel.
5. Analyzing the market using short-term channels can help us in anticipating the direction of the longer term channels.

Also, we have seen how we can use the Stochastic Slow Oscillator to help us in identifying turning points of the small channels and to use it on the bigger charts to anticipate the reversal of the bigger channels. Finally, we explained how to apply the momentum indicator on the envelopes itself to provide us with more information concerning the weakness or strength of the channels.

In the end, no one will ever have a definite view on the market because the market is simply inefficient, and if we all know where the market is going, it will correct itself and move in the other direction. Thus, this article is considered as a trial to help us look at the market in a clearer and more efficient way and finally to understand the reason behind the false breaks and randomness, or what we have called the Ripples Effect.

References

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Software and Data

Thomson Reuters Eikon
Metastock, Equis International, a Reuters company
MS Office, 2010 Microsoft office
Data provided by Refinitiv

Forecasting Major World Indices on Ichimoku

By Yukitoshi Higashino, MFTA

Yukitoshi Higashino, MFTA

742-18 Kayadamachi
Yachiyo-shi, Chiba-ken 276-0044
Japan

+8190-3499-4252
higashino3z@gmail.com

Abstract

Ichimoku is a technical analysis method developed by Goichi Hosoda (1898–1982), a Japanese financial market journalist, through his many years of research in financial markets. Even 30 years after Hosoda's death, Ichimoku is still widely used by traders and investors as an effective tool for analyzing markets and trade with in Japan. Hosada's grandson took over Ichimoku and has a study meeting every month in Tokyo.

Many of you may particularly know about "kumo (cloud)". However, although Ichimoku is starting to be popularized by an increasing number of traders and investors around the world, it does not seem to be utilized as widely and as effectively as it is in Japan. The reason is because Ichimoku is an integrated set of multi-faceted market analysis principles and techniques, including price projection, time projection, wave analysis, and more.

The wide variety of techniques and concepts included in the whole Ichimoku theory make it highly challenging to fully master. And, obviously, there is a language issue. Japanese is a tricky language for many Westerners. Japanese vocabulary is very different from English, and Japanese grammatical structure is also totally different than English, making translation from Japanese into English quite difficult. It is especially challenging to find the right English translations of many Japanese words used in the original Ichimoku theory. Therefore I have made an attempt to use plain English words instead of being "loyal" to the Japanese words in the original theory.

The following content revises my presentation at the IFTA Conference in Cairo and adds related theories to make it easier to understand for readers. I hope this will help IFTA colleagues learn the basics of a unique technical analysis method developed in Japan.

Introduction

- Ichimoku is focused on the underlying "powers" in the market. To know the next market direction, it suffices to know which side, buyers or sellers, is winning or losing. The market moves in the direction in which the equilibrium between the buyers and sellers has been broken. The chart developed by Hosoda allows one to instantly grasp the equilibrium state of the market. This is why it was named "Ichimoku Kinko Hyo," which literally means "One Glance Equilibrium Chart" in Japanese.
- The middle-point of the price range is regarded as important.
- The three basic components of the Ichimoku theory are the "time" principle, "wave structure" principle, and the "price level" principle.
- One of the important traits of Ichimoku is its "time" study. Most market players focus on price moves and tend to make light of the time factor. In Ichimoku, while price moves are important, the time factor is more important than the price factor; without a solid "time" study, one cannot have a true understanding of the markets.

Composition of the Ichimoku Chart

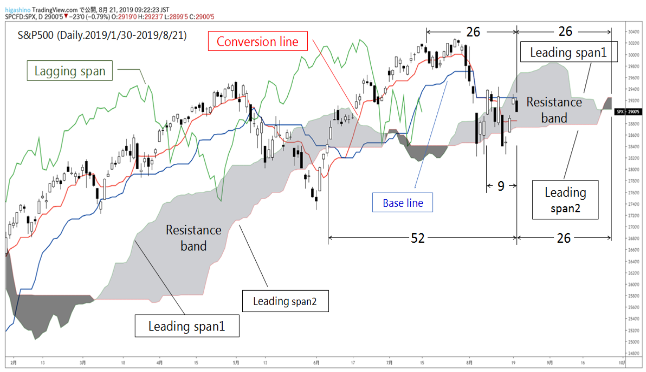
Figure 1 is a daily chart of the S&P 500. Ichimoku consists of a candle chart and five lines. Each five lines often serves as support or resistance.

The Conversion line is the middle-point of the high-low range in the last nine periods (including the current period), and the Base line is the middle-point of the high-low range in the last 26 periods (including the current period). They may look similar to moving averages, but they are different. They may be called "moving middle-points." In Ichimoku, it is considered that middle-points represent better equilibrium points in the market than moving averages. In moving averages, regardless of the volatility or the price swing in a given period, the closing price is the only thing that is counted. That is, even if the price swings vary widely in a period, it is not reflected. Ichimoku dismisses this and uses the middle-point indicators, whichinstead reflect the whole price range in a given period.

The Leading span 1 is the middle-point between the Conversion line and the Base line. The Leading span 2 is the middle-point of the high-low range in the last 52 periods (including the current period). Leading spans 1 and 2 are plotted 26 periods ahead (including the current period). The cloud-like area formed by the Leading span 1 and 2 is called the "Resistance band."

The lagging span is drawn by plotting the current closing price 26 periods backward (including the current period). It becomes a line which runs parallel to the current price line.

Figure 1. Composition of the Ichimoku chart



Three Conditions to Make a Safe Bull (Bear) Call

When the following three conditions are in place, one can safely judge that the market is in a bullish state. We call it "San'yaku Koten," meaning the market is ready to start an uptrend.

- The Conversion line is above the Base line, which is trending up or flat.
- The Lagging span is above the price of 26 periods ago.
- The price is above the Resistance band.

On the other hand, when three opposite phenomena are in place, we call it "San'yaku Gyakuten," meaning that the market is ready to start a downtrend.

- The Conversion line is below the Base line, which is trending down or flat.
- The Lagging span is below the price of 26 periods ago.
- The price is below the Resistance band.

Figure 2 is a daily chart of FB as a sample of "San'yaku Koten." As of (1), the Lagging span is above the price of 26 periods ago. As of (2), the conversion line is above the Base line. As of (3), the price is above the Resistance band. When these three conditions are confirmed, you can judge "San'yaku Koten."

Figure 2. Daily chart of FB as a sample of "San'yaku Koten"

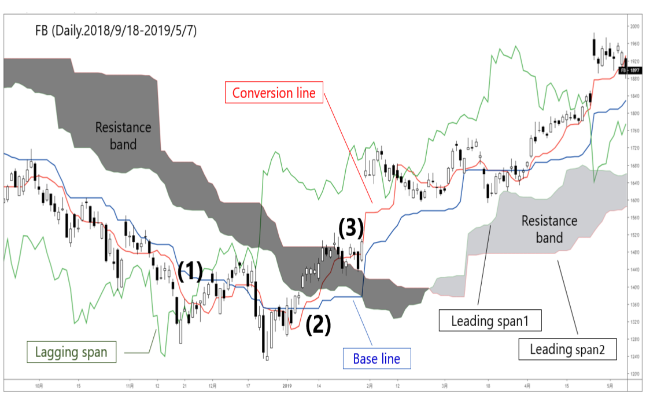
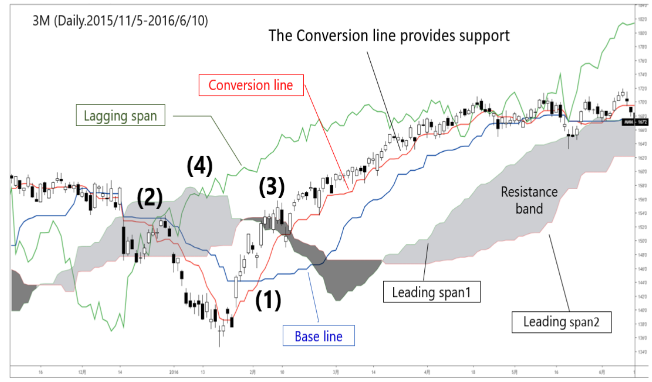


Figure 3 is a daily chart of 3M. (1) to (3) are the same sign; however as of (4), when the Lagging span is above the Resistance band, the momentum is often stronger. And, without falling to the baseline, the Conversion line provides continue to support price as strong market.

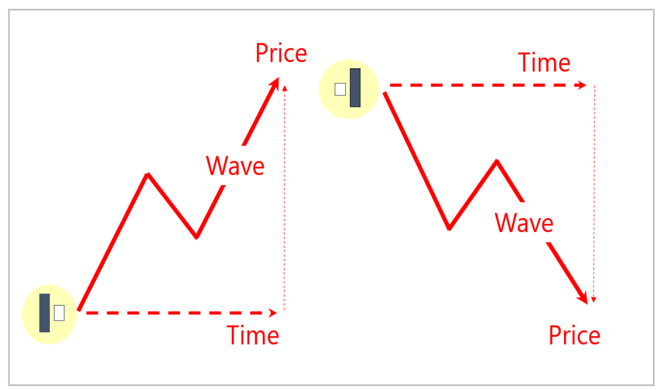
Figure 3. Daily chart of 3M as asample of "San'yaku Koten"



The Three Basic Principles of Ichimoku

After confirming San'yaku Koten, you should consider the three basic principles: "wave structure," "price level," and "time". Figure 4 shows all the points. Notice that the bull market consists of three waves, and an equilibrium is established between price and time. The same applies to the bear market. It is highly probable that the market direction will reverse at the equilibrium point of the horizontal and vertical axes.

Figure 4. The three basic principles of Ichimoku



Wave Structure Principle

First of all, the wave structure principle is very simple. Hosoda classified the wave patterns that appear in financial markets into a number of groups according to their wave structure and gave them unique names. I wave is a single rectilinear or straightish (normally sharp) thrust up or down without notable corrective moves. V wave consists of two successive I waves, a sharp thrust up followed by a sharp thrust down, or a sharp thrust down followed by a sharp thrust up. N wave is an up-down-up or down-up-down wave. This is the wave pattern most commonly seen in the market.

When N wave extends to nine waves, it is judged that the uptrend is close to the limit. And when the price falls below the previous low, the uptrend terminates with the top-forming pattern.

Figure 5. Wave structure principle

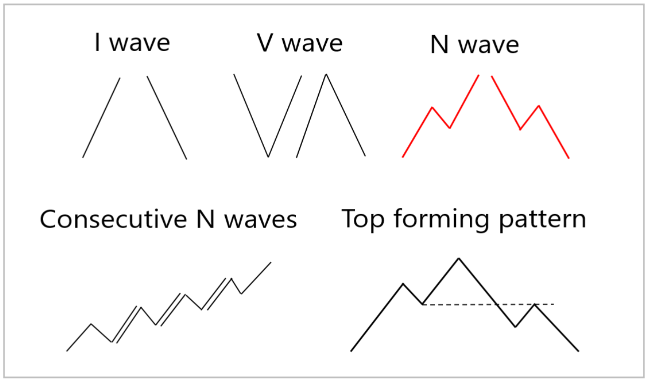
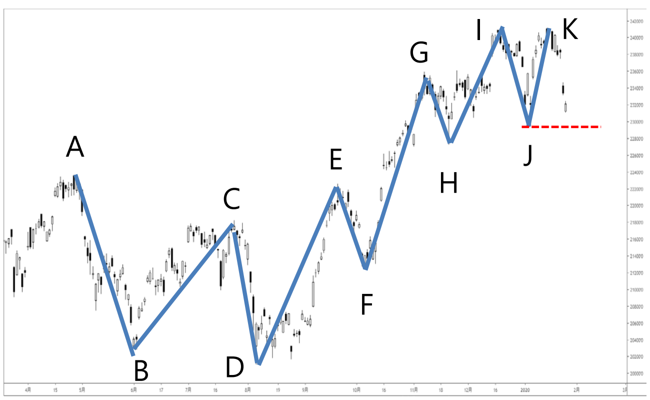


Figure 6 is a daily chart of the Nikkei Stock Average from March 19, 2019, to January 28, 2020.

- The wave from A to B is an "I wave."
- The wave from B to C is also an "I wave."
- The wave from A to C is a "V wave."
- The wave from A to D is an "N wave."
- The wave from D to K is an "N wave" structured upward wave. The uptrend would terminate if the price falls below the low J.

Figure 6. Daily chart of the Nikkei stock average



Price Level Principle

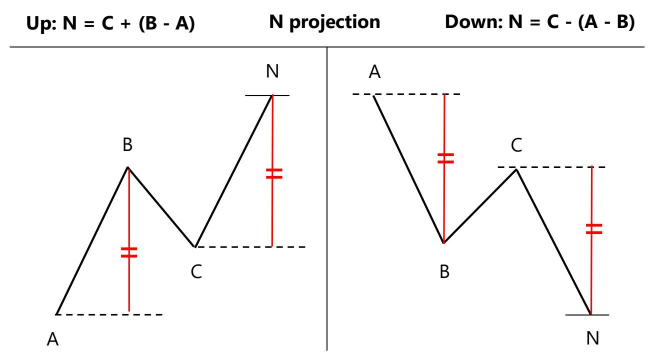
In ichimoku, there are four basic projection methods as shown below.

N projection -- Up: N = C + (B - A) Down: N = C - (A - B) [Figure7]

** These two equations are effectively the same, but I am showing both as I believe this makes it intuitively easier for readers to understand for. The same applies to the following.*

- Up: N projection adds the distance of the last upleg to the last low.
- Down: N projection subtracts the distance of the last downleg from the last high.

Figure 7. N projection

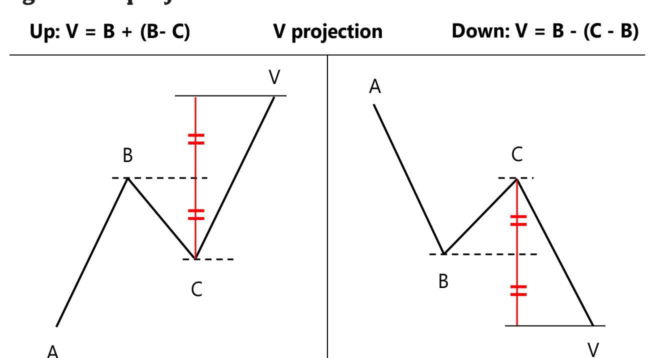


V projection – Up: V = B + (B - C) Down: V = B - (C - B) [Figure 8]

- Up: V projection adds the distance of the last downleg to the last high.
- Down: V projection subtracts the distance of the last upleg from the last low.

This is the target to sell half of the position.

Figure 8. V projection



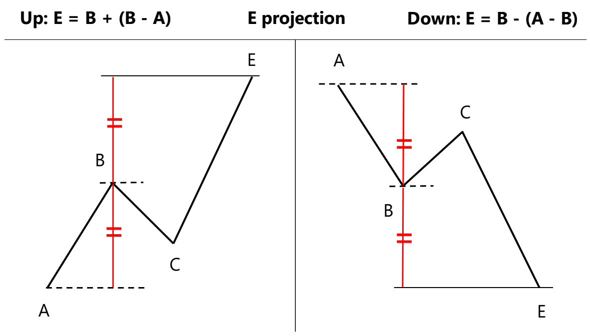
The target to sell half of the position

E projection – Up: E = B + (B - A) Down: E = B - (A - B) [Figure 9]

- Up: E projection adds the distance of the last upleg to the last high.
- Down: E projection subtracts the distance of the last downleg from the last low.

This is the target to sell all the positions.

Figure 9. E Projection



The target to sell all the positions

NT projection -- Up: NT = C + (C - A) Down: NT = C - (A - C) [Figure 10]

- Up: NT projection adds the distance between the last two lows to the last low.
- Down: NT projection subtracts the distance between the last two highs from the last high.

Figure 10. NT projection

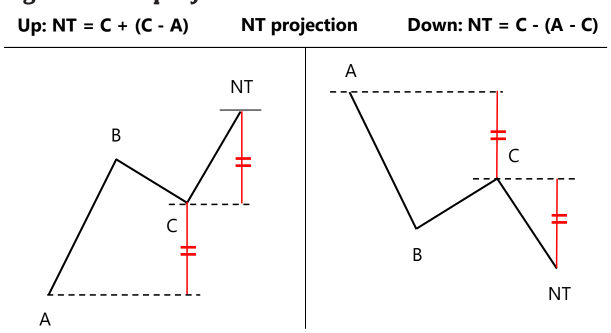


Figure 11 is a daily chart of Wisesoft, which is listed on the Shenzhen market in China. In a short-term wave, a high was reached at N projection of 18.77, and a correction was reached at E projection of 13.72. And then, it was reached at V projection of 16.35 with a smaller upward N wave, and a correction was reached at N projection of 12.7. Currently, you can see a larger downward N wave because it was below the previous low.

Figure 11. Daily chart of Wisesoft

In addition to the four basic projection methods (N, V, E and NT projection), it is also effective to use the middle-point of each projection.

Moreover, to project higher-degree targets, using the four basic projection methods, whole-number multiples of the distances used above (e.g., distances between previous highs and lows) are used (Figure 12). When the market is about to make a big move up, typically, those distances are multiplied by four to project higher targets.

Figure 12. Four times higher is the target in a big move up

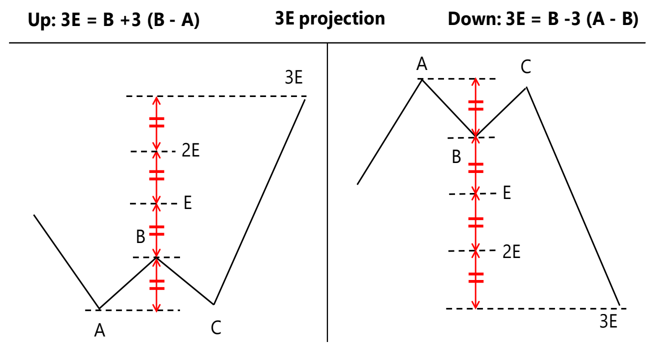


Figure 13. Downward wave of Amazon

Figure 13 is the downward wave of Amazon.com in the second half of 2018. The lower targets are multiplied by four in the initial range. When N wave extended to nine waves, the downtrend was over.

Habitual Price Range (applied type)

There is also an applied type that uses past price range to predict future price range (Figure 14). This is the idea that the price range from A to B and from C to D is the same.

Figure 14. Habitual price range (applied type)

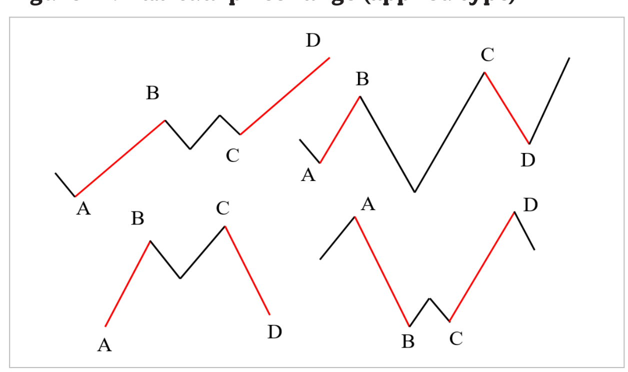


Figure 15 is a daily chart of ELSWEDY ELECTRIC, which is listed on the Cairo market. Although V, N, and E projections can be seen in various places, the left and right range excluding intermediate waves are almost the same.

Figure 15. Daily chart of ELSWEDY ELECTRIC

Time Principle

The third subject is the time projection. One striking characteristic of the Ichimoku theory is the degree of importance it places on the time factor. Hosoda taught, "It is not that time merely passes as prices fluctuate in the market. Time influences the market. The market is dictated by time."

Ichimoku calculates "Reversal dates" in the following "Basic number"-based projection and "Time parity"-based projection. These two methods can be used separately or simultaneously.

a) "Basic number"-based projection

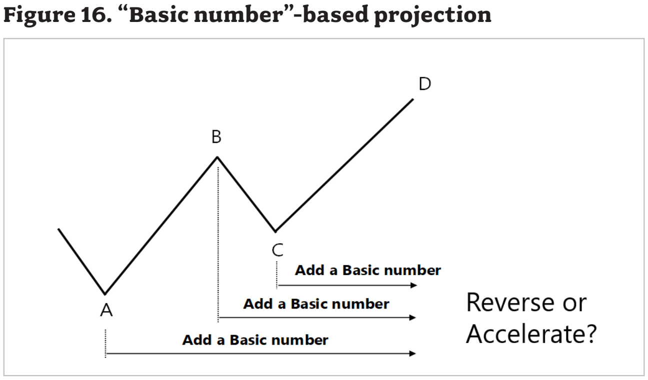
First, I explain "Basic number"-based projection. Following (Table 1) are the "Basic numbers" to be used with period data as default parameters. In addition to that, there are 83,97,101, etc. Some Ichimoku researchers claim that they have found that 5,13,21 should be added as Basic numbers when dealing with weekly data.

Table 1. "Basic numbers" to be used with period data

Basic number	Comments
9	-Useful for calling intermediate tops/bottoms
17	-Useful for calling intermediate tops/bottoms (9+9-1)
26	-First term, Useful in up markets (9+17)
33	-Particularly useful in down markets (17+17-1)
42	-Very important in both up and down markets (17+26-1)
51	-Second term (26+26-1)
65	-More useful in up markets than in down markets (33+33-1)
76	-Third term, More useful in up markets than in down markets (26+26+26-2)
129	-More useful in up markets than in down markets (65+65-1)
172	-More useful in up markets than in down markets (33+65+76-2)

Reversal dates are projected by adding "Basic numbers" to the high or low on which the trend reversed. Figure 16 illustrates this.

Figure 16. "Basic number"-based projection



Reversal dates are the dates on which the market is projected to "reverse" directions at relatively high probabilities. However, the market does not always "reverse" on a Reversal date. In a strongly trending market, the existing move sometimes simply "accelerates" instead of "reverses" on a Reversal date. This happens more often in a down-trending market than in an up-trending market. Suppose there is a market that has been moderately declining into a Reversal date. If it cannot reverse direction during that time window, oftentimes it starts falling sharply.

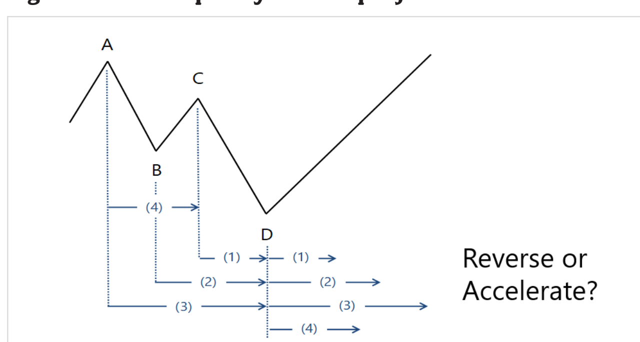
Figure 17 is a daily chart of CIMB Group, which is listed on the Malaysian market. It shows that the market direction changes when it reaches from a major low to a Basic number or a near Basic number.

Figure 17. Daily chart of CIMB Group

b) "Time parity"-based projection

Second is "Time parity"-based projection. In this method, Reversal dates are projected by adding the same time distance between two key dates in the past to the high or low on which the trend reversed, from which to project into the future. Figure 18 illustrates this.

Figure 18. "Time parity"-based projection



1. Add the time distance (the number of the days) between the high C and the low D to the date of the low D into the future.
2. Add the time distance (the number of the days) between the low B and the low D to the date of the low D into the future.
3. Add the time distance (the number of the days) between the high A and the low D to the date of the low D into the future.
4. Add the time distance (the number of the days) between the high A and the high C to the date of the low D into the future.

Basically Nine Patterns of "Time Parity"

There are basically nine patterns of taking Time parity numbers. Of these, three are shown in the circles(Figure 19). The left one means that the first I wave determines the V wave in the next identical period. And the right one means that the N wave determines the V wave in the next identical period.

Figure 19. "Time parity"-based projection

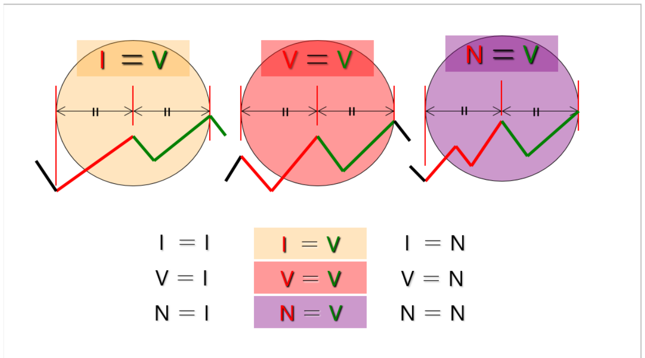
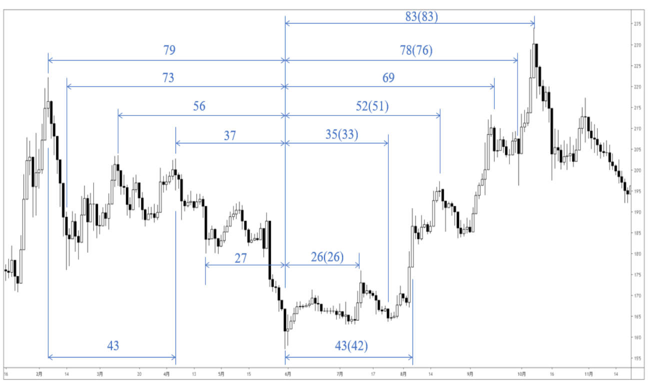


Figure 20 is a daily chart of SIDI KERIR PETROCHEMICALS (Sidpec), which is listed on the Cairo market. Starting from a low in May 2017, one would notice that the Time parity-based projection worked well to call market turns. Also, one would notice that the numbers are close to the Basic numbers. To be sure, separately run Basic number-based projection and Time parity-based projection often converge.

Figure 20. Daily chart of Sidi Kerir Petrochemicals



Coincidence Point of Time and Price Is the Important Reversal Date

Finally, I'd like to summarize the main point. Determine important Reversal dates such as reversal or acceleration by recognizing the coincidence point of the price target on the vertical axis and the time on the horizontal axis.

For example, in the upper diagram in Figure 12, the coincidence point of the price target calculated using N projection and the Basic number 76 from the low is the important Reversal date.

In the lower diagram in Figure 12, the coincidence point of the price target calculated using 2E projection and the Time parity number 81 from the low is the important Reversal date. "81" is the number of days in 29 and 53 V waves in the past N waves.

It means that the time parity number 53 does not coincide with price projection. Therefore, one should judge that after correction, the uptrend will continue until the coincidence point of time and price is reached.

Figure 21. Coincidence point of time and price

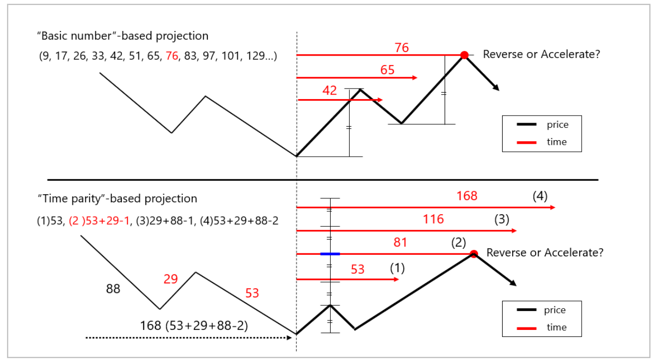


Figure 22 is a daily chart of ORIENTAL WEAVERS as a sample of the N projection. On the left side of the chart, the coincidence point of the number of the time parity 54 and the N projection in the N wave was the Reversal date for the upward wave. On the right side of the chart, the coincidence point of the Basic number 65 and the N projection in the N wave was the Reversal date for the next upward wave.

Figure 22. Daily chart of Oriental Weavers

I hope that you all have understood the relationship between the "wave structure," "price level," and "time" principles.

Forecasting Major World Indices

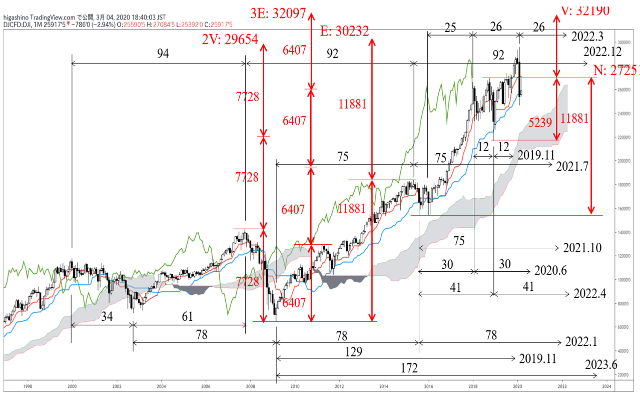
Dow Jones Industrial Average, Monthly

Figure 23 is a monthly chart of the Dow Jones Industrial Average. In July 2019, a high was reached at N projection of 27,251 dollars in N wave from March 2009. After that, the stock price dropped sharply; however, San'yaku Koten continued. And the conversion line has accelerated in October 2019; therefore, the market became more bullish. As a result of responding to changes in the conversion line, November 2019 was a significant acceleration point, as it was the month with the time parity 12 and the basic number 129.

And the 2V projection of 29,654 dollars from a low in 2009 was reached in February 2020. The February high was close to time parity number 25 from the January 2016 low to the January 2018 high. It is a basic number 26 in the first place. This means that the time and the price did coincide. After that, the stock price dropped sharply. If the market can stay San'yaku Koten after the correction, one should judge that the uptrend will continue until the coincidence point of time and price is reached again.

Basically, the points where the trend is likely to change are the timing when the Lagging span touches the stock price. If the Lagging span falls below the stock price, a bearish sign is confirmed. However, as with the 2016 correction, if the Lagging span jumps to support the stock price at that time (January 2014), the trend will be further strengthened.

Figure 23. Monthly chart of Dow Jones Industrial Average



If it exceeds the high in February 2020, it will be the ninth wave. The upside target is E projection of 30,232 dollars from the low in 2009. Also, there is V projection of 32,190 dollars in the period after 2018. This is an important target that consistent with 3E projection of 32,097 dollars from the low in 2009. And the most important timing on the time projection is from July to October in 2021, from January to April 2022, December 2022, and June 2023.

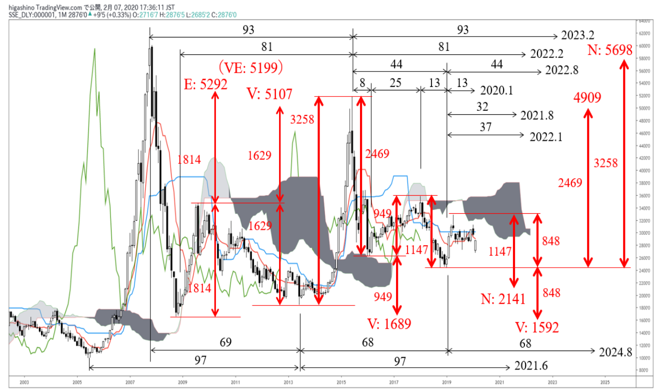
Shanghai Composite Index, Monthly

Figure 24 is a monthly chart of the Shanghai composite index. Look at the long-term N wave from a low in 2008. The coincidence point of 81 months close to the Basic number 83 and the middle-point(VE:5199) of E and V in the N wave was the reversal month for the upward wave.

Currently, it is moving in the downward wave from a high in 2015. In the short term, the Conversion line may go above the base line; however, it is not just San'yaku Koten. That is, the downward wave can be predicted to continue. In that case, the coincidence point of the time parity 81, 93, 97 and V projection of 1,689 in the N wave from a high in 2015 is likely to be an important reversal month for the downward wave. In addition to focusing on the move from a high in 2015, the time parity 13, 32, 37, 44 may also be important as the time on the horizontal axis. The downside target is V projection of 1,689 in the N wave from a high in 2015 as well as N projection of 2,141 and V projection of 1,592 in the N wave from a high in 2018.

If it exceeds a high in 2018 with San'yaku Koten, it is likely to lead to a larger N wave starting from a low in 2013. In this case, the month coming with the time parity 32, 37, 44, 68, 81, 93, 97 will be the important reversal month for the upward wave. And it is considered that the upward wave will continue until the N projection of 5,698 or the level of 4,909 obtained using the habitual price range.

Figure 24. Monthly chart of the Shanghai composite index



EGX30 Index, Weekly

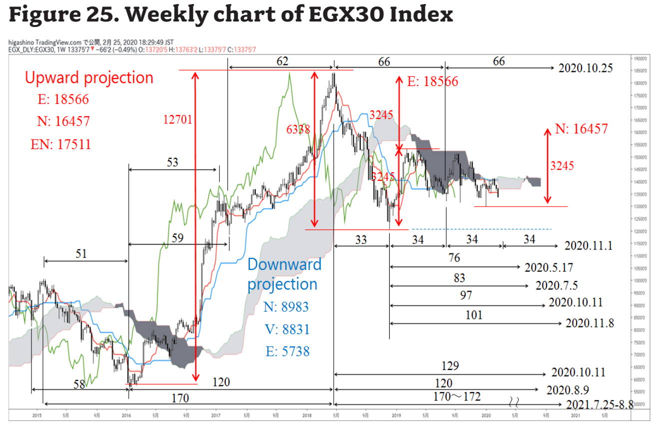
Figure 25 is a weekly chart of the EGX30 Index. Currently, it is a small-scale rebound from the low in December 2018. If it exceeds the high in February 2019, N wave from the low in December 2018 can be confirmed. And you can predict N(16457) and E(18566) upward projections. In addition, it is important to predict the middle-point (17511) of N and E projections. After the short correction, if it exceeds the high in April 2018, a larger N waves starting from the low in January 2016 can be confirmed. In that case, the price range of 12701 from the low in January 2016 to the high in April 2018 and the price range of 6338 from the high in April 2018 to the low in December 2018 will be an important factor for the price projection.

However, if it falls below the low in December 2018, the medium-term N wave starting from the high in April 2018 can be confirmed. And you can predict N, V, and E downward projections.

After 2020, what is important in the time projection is the time parity 34 for short-term wave and the time parity 66,120 for medium-term waves. In addition, the week coming with the basic number 76,83,97,101 from the low in December 2018 and the basic number 129,172 from the high in April 2018 will be the important reversal weeks.

I have just written about the future assumptions so far; however, what I want to say is, regardless of the size of N wave, whether it be an uptrend or a downtrend, it will continue until the coincidence point of time and price is reached.

Figure 25. Weekly chart of EGX30 Index

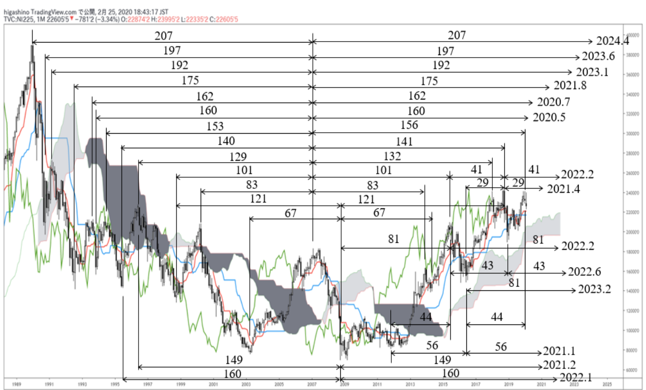


Nikkei Stock Average, Monthly

Figure 26 is a monthly chart of the Nikkei Stock Average. When you look left and right centering on a high in February 2007 and a low in October 2008, you will notice that the time parity numbers are major highs and lows. In this case, the months coming with the time parity 160–207 will be the important reversal timing for the upward wave or the downward wave.

And after a low in October 2008, what is important in the time projection is the time parity 29,41–44,56,81 for medium-term waves. If the price projection (N,V,E, etc.) is realized at the time parity 29,41–44,56,81 for medium-term waves, this will be the important reversal month.

Figure 26. Monthly chart of Nikkei stock average



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Stock Trends and Trend-Based Trading Strategies—Backed by Large-Scale Back-Testing Implemented by Automated Software System

By Kevin Luo

c/o NAAIM Founders Award
6732 W. Coal Mine Avenue #446
Littleton, CO 80123
Phone: +1 (888) 261-0787
Web: https://www.naaim.org

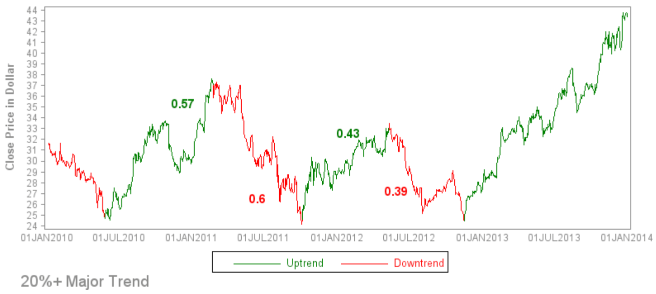
Introduction

The term "stock trends" may evoke many bright and dark images: rising Apple stocks, comeback of the NASDAQ Composite Index in 2014, meltdown of the financial sector in 2008, and more. What are stock trends? Do all investors who use stock trend analysis in their investment decision-making process have a clear view of their stock trends? It can always be argued if stock trends should be vaguely or precisely defined. It cannot be argued that vagueness creates gray areas. Gray areas grow uncertainties that can lead to serious risk problems. This paper describes and discusses a research project in which stock trends were quantitatively defined with a single factor, isolated, analyzed, and then summarized. The method is easy to approach. Its results are precise and black/white. The paper also demonstrates applications of the trend analysis with introduction of two trading strategies formulated based on a trend technique.

Trend Definition and Description

Edwards and Magee (2007) have developed some exclusive frameworks for trend analysis based on the Dow Theory. According to Edwards and Magee, there are two decisive factors in trend determination. They are price movement and time frame of such price movement. In terms of "primary trend," it is "appreciation or depreciation in value of more than 20%" and "last for a year or more" (Technical Analysis of Stock Trends, Edwards and Magee, 2007, P15). This approach provides some ultimate leads for practical applications of stock trend analysis. Among the two trend decisive factors, price movement is obviously independent and time frame is dependent. Time frame is an important factor; however, it sometimes creates confusion. Questions would definitely be raised when a market declines 20% and then climbs right back in less than one year. Do we classify the price movement as a stock trend? Can money be made or lost during the price movement just like in a "qualified" primary trend? Would trend analysis still work without the time frame? A research project was conducted to isolate and analyze stock trends without the time frame factor. In the project, two types of trends were defined. Uptrend is recognized in case prices move upward more than 20% and downtrend is recognized in case prices move downward for more than 20%. The definitions are practically identical to the condition of "appreciation or depreciation in value of more than 20%" by Edwards and Magee. A sample trend chart is exhibited in Figure 1.

Figure 1. Trend chart sample. *Source: Archer Daniels Midland Co. (ADM)*



The close prices in green belong to the uptrends and the close prices in red belong to the downtrends. Each trend has its beginning and ending prices, which are jointly used by linking trends. The numbers (in 100%) on the chart represent trend sizes of the respective trends. Trend size is the vertical distance between beginning and ending levels of a trend divided by the beginning or ending price. Using the term "trend size" is an attempt to differentiate the concept from existing terms such as "trend length," which factors in time frame. In terms of equations, trend sizes are:

1. Uptrend Size = (Ending Price – Beginning Price) / Beginning Price
2. Downtrend Size = (Beginning Price – Ending Price) / Ending Price

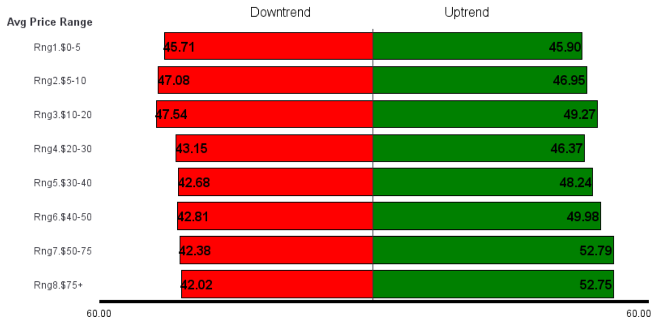
Please refer to Appendix One of the Appendices Section for details regarding the difference of uptrend and downtrend calculations.

Trend Isolation and Trend Characteristics Analysis

To prove that the trend analysis with only price factor still works, the project was designed to isolate stock trends from a large number of stocks and then summarize trend characteristics, which are in turn to be used in the trading strategy development. If the developed strategies work, the trend analysis works. As the larger scale leads to increased precision and reliability, 1,816 random stocks were selected for the research. These stocks were all listed on NYSE and NASDAQ. Standard daily price data (open, high, low, and close) was used. Data range covered an approximately 10-year period of time from January 1, 2005 to September 1, 2014. Tasks of the project such as trend isolation, characteristics summarization, back-testing, and graph generations were automatically implemented by a custom-designed software system (the software).

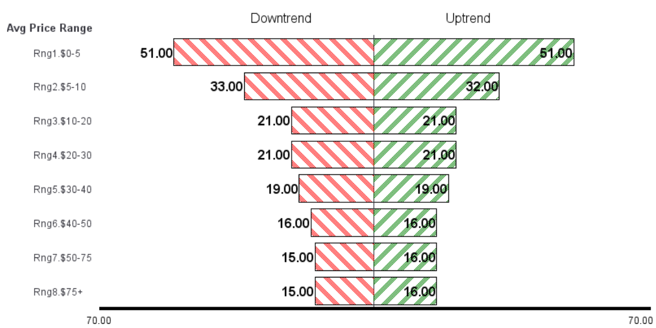
In the trend isolation process, the software separated 88,353 stock trends from 1,816 stocks. Figure 2 shows the average trend sizes by different price range groups. On average, the uptrend size measured 48.29% and the downtrend size measured 45.37%.

Figure 2. Average trend size (%) by stock price group



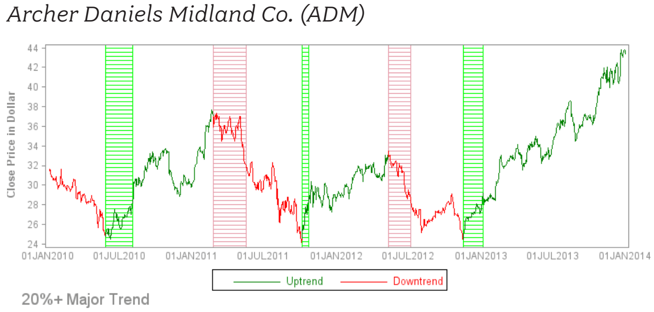
The study found no evidence that the cheaper stocks produce the larger trends; however, as shown in Figure 3, the cheaper stocks did generate larger trend counts than the expensive stocks. The stocks priced under $5 produced approximately three times more uptrends and downtrends than stocks priced over $40 on average. This probably means that the cheaper stocks tend to move up and down more frequently. Therefore, it is reasonable to conclude that the average uptrend size of 48.29% and downtrend size of 45.37% represent the stocks in all price ranges.

Figure 3. Average trend count by stock price group



In practice, a trend is not recognized until it is confirmed. The confirmation requires a stock to move a minimum of 20% in a direction. The confirmationportion of the trend is called "confirmation section" in this paper. In Figure 4, the sample uptrend confirmation sections are covered by the green shades and the downtrend confirmation sections are in the red shades.

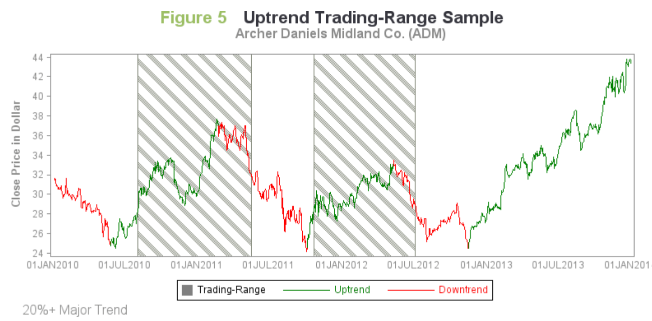
Figure 4. Trend confirmation section sample. *Source: Archer Daniels Midland Co. (ADM)*



One of the important findings in the research is that stocks tend to move substantially further beyond confirmation sections. Among interpretations of this finding, one stands out certain and clear. There must be good trading opportunities for the remaining section of the typical trend. The remaining section ends when the trend reverses. For the typical uptrend, it covers 28.9% of the uptrend (after the confirmation section) and 20% of the following downtrend (or the downtrend confirmation section). Trading strategies may be developed targeting the 28.9% in the uptrend or the

entire remaining section. In this research project, two sample trading strategies were formulated targeting the entire remaining section. The remaining section is labelled as "trading range" in this paper for convenience. A sample of uptrend trading ranges (gray-shaded sections) is displayed in Figure 5. Next, the paper details the strategy development and back-testing of two trading strategies. The back-testing of the strategies determines effectiveness of the trend analysis.

Figure 5. Uptrend trading range sample. *Source: Archer Daniels Midland Co. (ADM)*



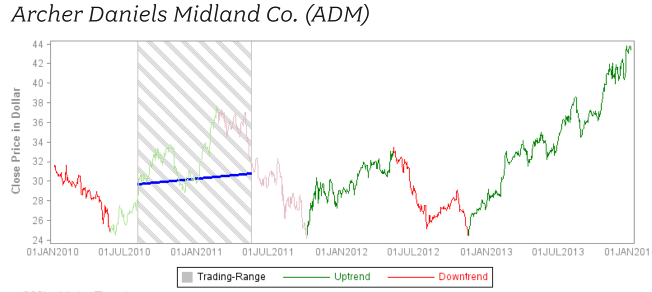
Trading Range Strategy

Strategy

In this paper, trading strategy is defined as a set of methods or techniques that can be independently and repeatedly used in trading operations.

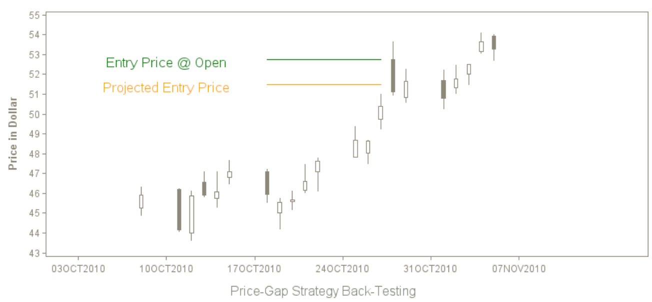
Trading Range Strategy was formulated based on the trend characteristics obtained from the trend analysis. The strategy aims to maximize per-trade profit with a few simple rules. As stated, the average uptrend is measured at 48.29%, which is more than twice larger than a confirmation section. One of the strategy ideas was to take and hold a position for the whole trading range. Figure 6 illustrates a sample trade of the strategy. The blue line connects buy and sell points. It is important to note that this strategy only allows trades in the trend directions. Only long trading is discussed in this paper.

Figure 6. Trading Range Strategy trade sample. *Source: Archer Daniels Midland Co. (ADM)*



Mathematically, after taking 40% out of both confirmation sections, there is still 8.29% left. This 8.29% is the theoretical per-trade profit for the strategy; however, assuming 8.29% as a figure close to the practical profit is very risky because the trading is in the same directions with the stock trends. In many cases, price actions such as open-gaps would easily wipe out all of the profits. In Figure 7, the sample shows the impact of an open-gap at the entry. Without the open-gap, the entry would have been recorded at the projected entry price (orange-line level). With the open-gap, it cost around $1.50 more to get in the long position (green line level). According to the statistics, 32.43% of trades were affected by open-gaps. Sometimes the open-gaps are very large. Skipping all open-gaps that cause higher than projected entries is a practical alternative; however, such attempts often end up losing good opportunities at the same time.

Figure 7. Open-gap impact on entry price sample. *Source: Akamai Technologies Inc. (AKAM)*



It is possible but unlikely for a simple strategy like Trading Range Strategy to work well on all stocks and all the time. It is necessary to select some suitable stocks from the random stocks for the back-testing. In theory, the larger the trend is, the greater the profit is. The suitable stocks for this strategy are considered as those with the larger trends. To confirm the theory, the research selected the top 500, top 200, and top 50 stocks at the top of a trend size sorted list. The back-testing generated summary statistics separately for the portfolios. These trading portfolios are labelled as Top-500 Portfolio, Top-200 Portfolio, and Top-50 Portfolio. The stock prices in the portfolios average $21.81, $19.94, and $13.83 for the Top 500 Portfolio, Top 200 Portfolio, and Top 50 Portfolio, respectively. The average trend sizes are 51.67%, 54.13%, and 56.12% for the respective portfolios.

Back-Testing

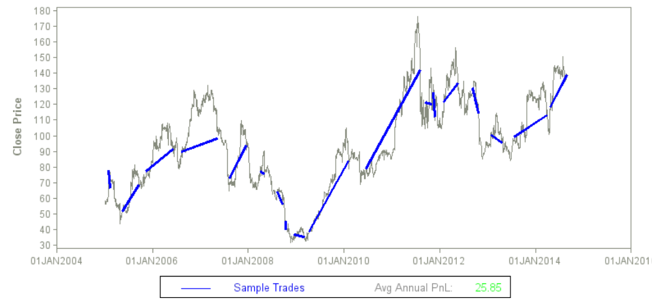
Back-testing is one of the most effective approaches for new strategy evaluations. In the back-testing of this project, the software tests each of the stocks individually by generating trades according to the trading rules and then summarizes the test outputs by the trading portfolios. No costs or volumes are factored in.

There are a couple of rules for the test:

1. Enter a long trade at the first available price after each of the uptrends is confirmed.
2. A trade exits at the first available price after the uptrend reverses or at the end of the test. Close price is used for liquidating a position at the end of the test.

A set of test trade samples are graphically presented in Figure 8. The blue lines connect buy and sell points of the trades.

Figure 8. Trading Range Strategy back-testing sample output. *Source: MicroStrategy Inc. (MSTR)*

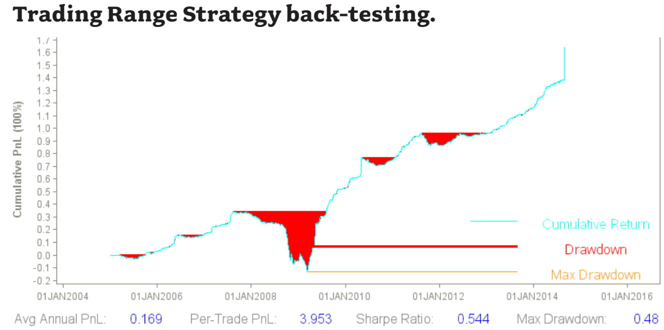


After implementation of the test tasks, the software produced some summary statistics for evaluation. The computation approach and equations are discussed in Appendix Two of the Appendices section.

Back-Testing Outputs

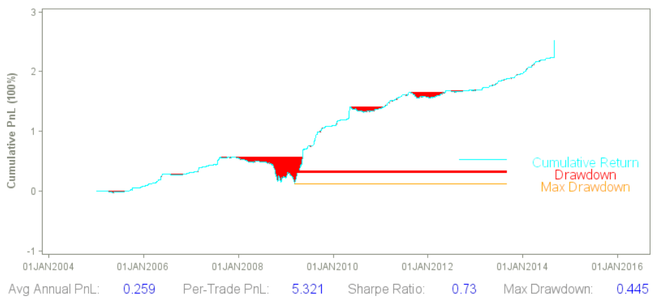
The software generates a set of performance statistics, including cumulative P&L, drawdown (graphically presented in charts of the Figures), average annual return, average per-trade return, Sharpe ratio, and max drawdown (in footnotes of the figures). In Figure 9, the summary shows that the strategy generated a 16.90% average annual return for the Top 500 Portfolio. The per-trade returns averaged at 3.95%, which is much smaller than the theoretical figure of 8.29%. The Sharpe Ratio was computed based on annual returns. The figure was calculated as 0.54. On the risk side, the max drawdown was recorded as 48.00%. Surge of the cumulative return in the end of chart was resulted from liquidating all positions described in Rule 2 of the back-testing. The software books profit/loss of the test trades at the exits.

Figure 9. Back-testing performance (500 stocks); Trading Range Strategy back-testing.



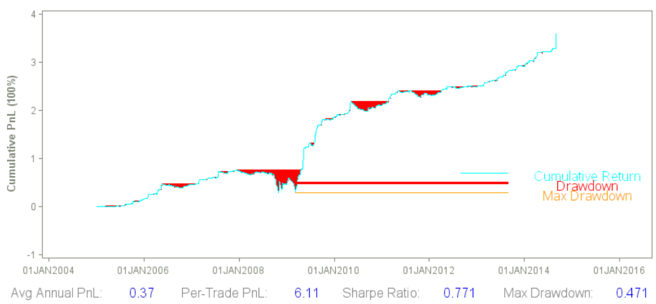
For the Top 200 Portfolio, the average annual P&L arrived at 25.90% which, as expected, is approximately 50% higher than the return from the Top 500 Portfolio (Figure 10). The average per-trade return is also higher by approximately 35% at 5.32%. The Sharpe Ratio and max drawdown are and 44.50%, respectively.

Figure 10. Back-testing performance (200 stocks); Trading Range Strategy back-testing



In Figure 11, the test performance for the Top 50 Portfolio is presented. The strategy worked better for this portfolio than the Top 200 Portfolio by 42%, as the average annual return reached 37.00%. The per-trade return of 6.11% is also greater than the 5.32% of the Top 200 Portfolio. The Sharpe Ratio is 0.77 and the max drawdown is 47.10%.

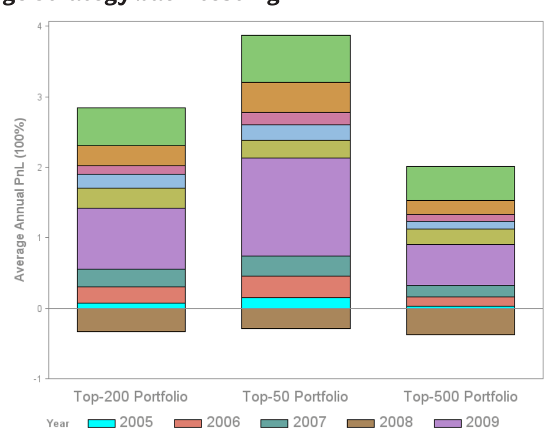
Figure 11. Back-testing performance (50 stocks); Trading Range Strategy back-testing



Evaluation

Evaluation of the Trading Range Strategy focuses on the back-testing performance, including returns and risks. Comparing returns among thethree portfolios can determine if there is a tendency for stocks with the larger trends to outperform other stocks. As shown in Figure 12, the Top 200 Portfolio outperformed the Top 500 Portfolio and the Top 50 Portfolio topped the Top 200 Portfolio by visible amounts consistently throughout the years. It confirms that there is a positive relationship between the stock trend size and the performance for the strategy. Knowing this relationship is helpful in future optimization and trading operations.

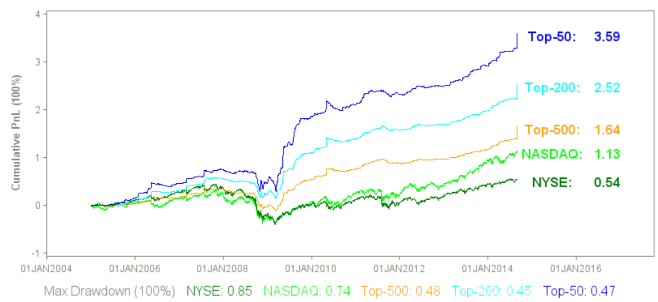
Figure 12. Test returns by portfolio and year; Trading Range Strategy back-testing



Using a stock index as the benchmark for the performance comparison may cause concerns in this case because this strategy involves frequent trading; however, such comparison does make some sense at this level of evaluation. This research puts performance statistics of the back-testing and two stock composite indices together for the comparison and evaluation. The two stock composite indices are NASDAQ (^IXIC) and NYSE (^NYA) of which the stocks in the back-testing belonged to.

In comparison of the cumulative returns, it appears that the portfolios outperformed the indices most of the time (Figure 13). The slopes of the cumulative return curves for the portfolios could have been adjusted steeper upward for 2012–2014 if the unrealized profits (the pop-up amounts in the end of the curves) were accounted for.

Figure 13. Test performance comparison; Trading Range Strategy vs. indices



Observations from Figure 13 (or Figures 9–11) also indicate that the strategy took some large losses. The drawdown readings reached as low as 48% for the Top 500 Portfolio. Those drawdown figures were primarily driven by the substantial declines of overall markets during 2008–2009. Under such market conditions, the uptrends shrunk and the larger open gaps at the exits pushed the returns further in the red. There is no easy fix for this issue unless adding managerial techniques such as long/short strategy or optimizing the trading model. On the bright side, the losses were not as bad as the indices suffered. The indices have carried up to 74% and 85% drawdowns throughout the period of time. This resulted from the trading on the uptrends only. The stocks have stayed on the sideline during the larger-than-average downtrends.

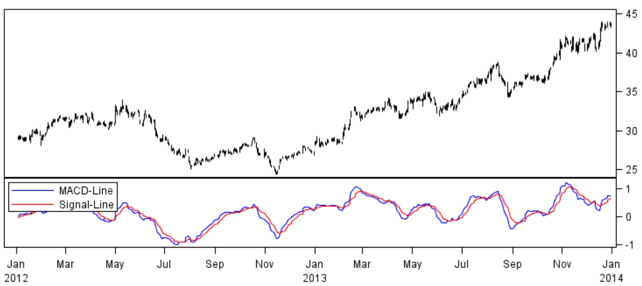
MACD Strategy

Back-testing results of Trading Range Strategy have proved that there are good opportunities for trading range in the trend analysis. Now the question is to what extent this trend technique can be applied. Here is another example strategy that connects trading range with one of the popular technical indicators, Moving Average Convergence/Divergence (MACD). This strategy is called MACD Strategy because MACD is the main base of the strategy.

Created by Gerald Appel, MACD is considered a simple and effective momentum indicator. MACD signal line crossover is a method showing bullishness and bearishness of the prices. A bullish crossover occurs when the MACD line rises and crosses the signal line from below. A bearish crossover happens when the MACD line falls and crosses the signal line from above.

According to statistics obtained from the trend analysis of the 1,816 random stocks, the average price changes (calculated as Close today – Close Prior in percent) are 2.18% and -1.92% for the bullish and bearish crossover days, respectively. These figures are considered significant when compared to 0.44% and -0.55% of price changes for the typical uptrend and downtrend day. It appears that MACD timely signals bullish/bearish price momentums. Can the signals be used as trading signals for long/short stocks? A back- testing was conducted to find the answer to the question. Test rules for long trades were buying at bullish crossover and selling at the following bearish crossover. The rules for short trades were shorting at bearish crossover and covering at the following bullish crossover. Close prices of the signal days were used as entry and exit prices. A timing sample is exhibited in Figure 14. The up arrow points to a bullish crossover and the down arrow points to a bearish crossover.

Figure 14. Sample MACD signal line crossover timing



Back-testing of MACD signal line crossover was implemented by the software that generated long or short trades for each crossover of the stocks. The average annual return for the long trades is 1.45% but the short trades lost (15.94%) annually on average. A finding of this research suggests that there are a large number of short trades in the uptrends and long trades in the downtrends. MACD is a good momentum indicator as the statistics suggest; however, the momentum signals generated by MACD are probably too frequent for a normal low-frequency trading strategy.

When trading against the trends too often over time, the profits are expected to be poor. Trading range is supposed to be capable of reducing some of the unfavorable trades to improve the performance. Another back- test was conducted with the trading range technique factored in. A couple of new rules were added.

1. MACD long trades are only allowed in uptrend trading ranges while short trades are only allowed in downtrend trading ranges.
2. At the end of the trading ranges, all holding positions are liquidated at the close price of the day.

Impacts of the trading range technique can be easily observed by comparing sample test trades shown in Figure 15 and Figure 16.

Figure 15 indicates the short trades generated without trading range for Allegheny Technologies Inc. (ATI). In Figure 16, the chart shows the short trades for ATI with trading range added. The trade count reduction is significant and the performance improvement from -10.71% to 7.30% is impressive.

Figure 15. MACD strategy short trades. *Source: Allegheny Technologies Inc. (ATI)*

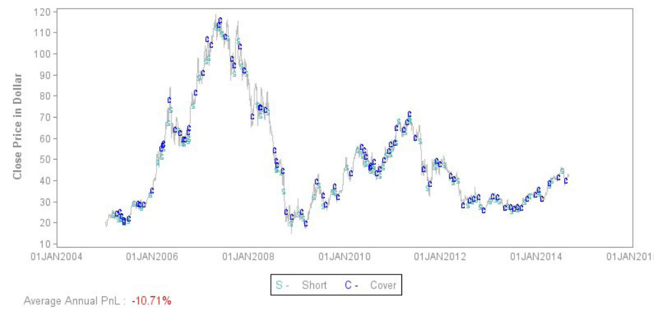
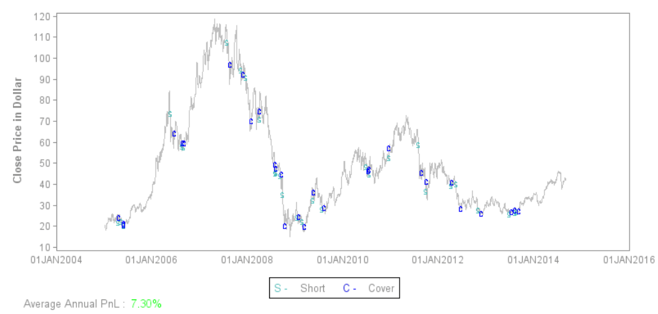


Figure 16. MACD strategy short trades with trading range. *Source: Allegheny Technologies Inc. (ATI)*



The summary of the second test shows that trading range improved the long trading return by 9.97% and the short trading return by 43.71% for the 1,816 random stocks. For the Top 200 Portfolio, the average annual returns were recorded as 16.82% for the long trades and -8.34% for the short trades. The test results are strong enough to conclude that the trend technique can be effectively incorporated with external strategies for performance improvement.

Conclusion

Success in testing the strategies suggests that stock trends defined with price factor alone worked effectively. The trend characteristics analysis offers valuable statistics for many areas of the investment decision-making process. It is easy to approach and does not require a great deal of effort to understand. Outputs of the trend analysis are precise. There is no gray area of confusion. From a strategy design standpoint, the trend analysis offers great flexibilities. Stock trends can be isolated into major, intermediate, minor, or custom-defined trends to meet user needs. There is huge potential for the techniques to grow in new strategy development and existing strategy improvement.

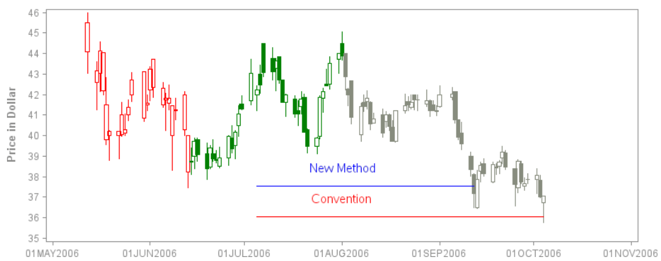
Trading Range Strategy is one of the simplest but most effective trading strategies. It is straightforward and easy to follow. There is large room for optimization of the strategy. Through the introduction of MACD Strategy, this paper has shown how effective the trend techniques can be in terms of incorporating with an external strategy. Results from the separated projects have confirmed that trading range technique also worked well with some other technical indicators such as RSI.

Appendices

Appendix A

Conventional calculation of downside percentage works for the majority of situations, but not the downtrend calculation in this research. The easiest way to describe the problems is to show an example (Figure A1).

Figure A1. Downtrend calculation method comparison
Source: Archer Daniels Midland Co. (ADM)



In this case, the stock starts to move lower after reaching the uptrend (green bars) high. By the conventional method, which is expressed in Equation 1 at the end of this paragraph, the uptrend would not reverse until the stock reaches approximately $36 (red line level in chart). That level is significantly lower than where the uptrend begins. It is reasonable to assume that this is a major concern for the majority of the trend users. To fix the problem, this research employed an alternative method which utilizes an easy equation (Equation 2). With this equation, an uptrend reversal level never falls below its beginning level anymore (blue line level in Figure A1). More importantly, the alternative method makes the trend analysis more meaningful. Under the convention, the maximum size for a downtrend is 100%. It is not comparable and combinable with an uptrend because the uptrend can be measured up to infinity percent. Without the alternative method, simple strategies such as Trading Range Strategy would have been more difficult to formulate. In this research, all statistics tied to downtrend measures were computed based on the alternative method.

1. Downtrend-Size (Convention) =
   (Ending Price – Beginning Price) / Beginning Price (100%)

2. Downtrend-Size (Alternative) =
   (Beginning Price – Ending Price) / Ending Price (100%)

Appendix A

Back-testing returns are expressed in two different ways. The first one is average per-trade method, which is very straightforward. The equations used in the calculations are exhibited below.

1. Per-trade P&L =
   (Exit Price – Entry Price) / Entry Price (100%)

2. Average per-trade P&L (trading portfolio) =
   sum of all per-trade P&Ls (all stocks) / Number of Trades (all stocks)

For the purpose of comparison, test results are also calculated conventionally. It utilizes equal-weighted approach, in which $1,000 is assigned to every trade regardless of share prices. The related equations are listed below.

1. Number of Shares (Trade) = $1,000 / Entry price

2. P&L (Trade) = Exit Price * Number of Shares - $1,000

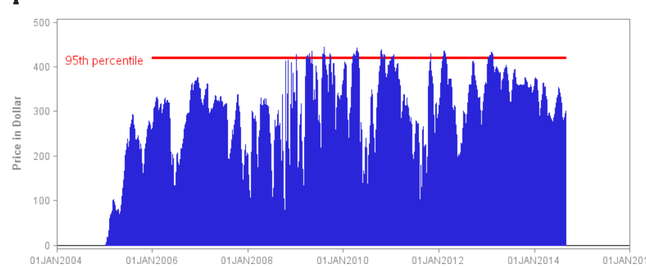
3. Daily P&L (Portfolio) = P&Ls (All Daily Completed Trades) / Portfolio Value (100%)

4. Cumulative P&L (Portfolio) = (Cumulative Daily P&L (Prior to A Given Day) + Daily P&L (A Given Day)) / Portfolio Value (100%)

5. Average Annual Return (Portfolio) = End-Test Cumulative P&L / Years (100%)

Because there were no cost or volume factors in the performance computation, the process was simplified by using a fix value as "Portfolio Value." "Portfolio Value" is computed based on stock counts in a portfolio. Trading a portfolio of stocks requires less capital to operate than holding the same stock portfolio. It is unreasonable to use full counts of stocks for "Portfolio Value" computation in this case. The chart in Figure A2 shows the stock holding counts for the back-testing of Trading Range Strategy.

Figure A2. Number of holdings—Top 500 stocks; Fixed portfolio value calculation



The less it holds, the smaller the capital needed to operate. For this research project, the 95th percentiles were used for "Portfolio Value" calculation. In this particular example, the 95th percentile (red line level in Figure A2) is 420 counts. "Portfolio Value" is therefore calculated as $420,000 ($1,000*420). $1,000 is the amount assigned to each trade. The figure is smaller than $500,000 ($1,000*500) for a holding portfolio.

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Simple and Effective Market Timing With Tactical Asset Allocation

By Lewis A. Glenn, Ph.D.[1]

Lewis A. Glenn, Ph.D.
Chief Scientific Officer
Creative Solutions Partners Associates
702 Park Hill Rd.
Danville, CA 94526 US
lewglenn@gmail.com
Phone: 925-820-5158

Abstract

A simple market timing algorithm is examined that switches from an exchange traded fund representing

U.S. equities to one holding treasury long bonds every month on the last day, the switch being made to whichever ETF has the greatest ratio of current adjusted closing price to adjusted closing price μ months earlier. The parameter μ is determined so as to maximize total return and minimize the total number of trades, however the results are relatively insensitive to μ over a fairly wide range. The performance of this scheme is compared to that of an Ivy 5 portfolio consisting initially of equal dollar amounts of ETFs in U.S. equities, foreign large blend, 7–10 year treasuries, real estate, and commodities. As with the paired switching approach, each ETF is purchased only once a month, on the last day, in this case only if its adjusted closing price exceeds the 10-month simple moving average (SMA). Otherwise, that portion of the portfolio is invested in a cash surrogate.

Comparison is made over the 10-year period ending on 12/31/13. It is shown that the average annual return of the paired switching algorithm exceeds 30% in this period, which is three times greater than that of the Ivy 5. Moreover, only 45 trades were required for the paired switching approach, whereas the Ivy 5 required 70 in the same period. The maximum draw down was 14.6% for the Ivy 5 and 18.8% for paired switching.

Introduction

The so-called weak form of efficient-market theory (EMT) holds that future stock prices cannot be predicted on the basis of past stock prices[2]. Many advocates of this theory believe that the best strategy for the long-term investor is to "buy the market," by which they generally mean to invest in an index fund that represents all, or a significant segment of, the equity market. The claim is that past performance has shown that in the long run buying and holding this class of asset will outperform any active management scheme.

One problem with this approach is the definition of the term "long run." To paraphrase the famous British economist John Maynard Keynes, "…in the long run we're all dead." In fact, many investors would consider a 5–15 year investment as long-term, whereas some would choose a period as long as 30 years and others as short as six months. A brief look at the large cap growth ETF (QQQ) that tracks the NASDAQ 100 (which consists of the largest non-financial securities listed on the Nasdaq Stock Market) exhibits what can happen over a long run. An investor purchasing this fund at its inception in March 1999 would have seen her investment more than double in the first year. Two and a half years later, by September 2002, this would have dropped by more than a factor of five and her holdings would be down to less than half the initial investment. It would take five more years for this investor to recoup the original investment, not including the interest she would have made had she remained in cash. Her willpower would once again be tested as she watched the collapse of the financial markets in 2008, by the end of which the value of the initial investment would be once again halved.

It is this scenario that tactical asset allocation seeks to mitigate. The main idea is simply to diversify portfolio assets and employ a market timing solution. But what kind of solution? The literature is replete with different approaches. Our goal here is not to review the many ideas that have been suggested but rather to focus on two very simple schemes.

An especially popular method was described by Faber[3] and then further elaborated by Faber and Richardson[4] as the Ivy 5 portfolio. The basic idea is to create a portfolio of five sectors consisting of the S&P 500 index, the MSCI EAFE index, U.S. 10-year government bonds, a real estate index, and a commodity index. The initial study involved non-tradable indices over a 35-year period. The trading rule was simply to buy each index when the monthly price exceeded the 10-month simple moving average (SMA) and to sell and move to cash otherwise. All entry and exit prices were on the day of the signal at the market close and the model was only updated once a month on the last day. Price fluctuations during the rest of the month were ignored.

Moving average methods are very useful for discerning trends and indeed this author has suggested several market timing algorithms based on them.[5,6,7] All moving average algorithms, however, exhibit latency, namely, they introduce some lag in the calculation so that the MA lags the original signal. This means that the user will implicitly be late in leaving a declining market and, perhaps even worse, late in entering a rising one. The lag time increases directly with the length of the moving average. The paired switching method to be described here does not depend on moving averages. In general, paired switching refers to investing in one of a pair of negatively correlated assets and periodic switching of the position on the basis of the relative performance of the two. Maewal and Scalaton[8] proposed an especially simple version that looked at the performance over a prior 13-week period and purchased the asset that had the higher return over that period. That position was then held for 13 weeks at which point the cycle was repeated. They looked at several different ETFs that served as surrogates for equities and bonds, including SPY (for the S&P 500) and TLT (for treasuries with maturities of 20 or more years).

Cohn[9] devised a similar scheme but employed it on a daily basis. Instead of a look back period of 13 weeks (65 trading days), he found that 84 trading days produced the best results.

In what follows we first generalize the Maewal-Scalaton procedure by switching between SPY and TLT in the same way as with the Ivy 5, namely once a month on the last day, the switch being made to whichever ETF has the greatest ratio of current adjusted closing price to adjusted closing price μ months earlier. The parameter μ is determined so as to maximize total return and minimize the total number of trades. We then compare the results to those obtained with the Ivy 5 portfolio over a recent 10-year period and exhibit the results in a novel way that allows an investor to immediately visualize end-of-period performance based on date of first entry (purchase) with use of the algorithm.

The Paired Switching Strategy

First, a few definitions are in order. Let the value of the paired switching portfolio on day n be $v(n)$, $1 \le n \le N$ and the normalized value be $V(n) = v(n) / C$, where C is the cost basis. For the 10-year period ending 12/31/13, $N = 2517$ trading days. Also, let $\tau(n)$ be the number of trades, where either a buy or a sell is considered a trade.

For a buy and hold (BAH) strategy with an individual ETF, the normalized value on day n is simply $V_{ETF}(n) = P_{ETF}(n) / P_{ETF}(1)$, where $P_{ETF}(n)$ is the adjusted closing price on day $n \ge 1$.

Then, the paired switching rule is simply:

Move to TLT on day n if and only if

$$V_{TLT}(n) / V_{TLT}(n - \hat{\mu}) > V_{SPY}(n) / V_{SPY}(n - \hat{\mu}) \qquad \text{Equation 1}$$

where $\hat{\mu}$ is the daily equivalent of μ. Otherwise, move to SPY. On all other days the previous position is maintained. Note that daily price data on both SPY and TLT are available since 7/30/2002.

Nominal trading costs are included on all transactions, but these costs are generally negligible with electronic trading and the high volumes extant with these ETFs. However, slippage is not included, and this might be significant with increasing trading frequency.

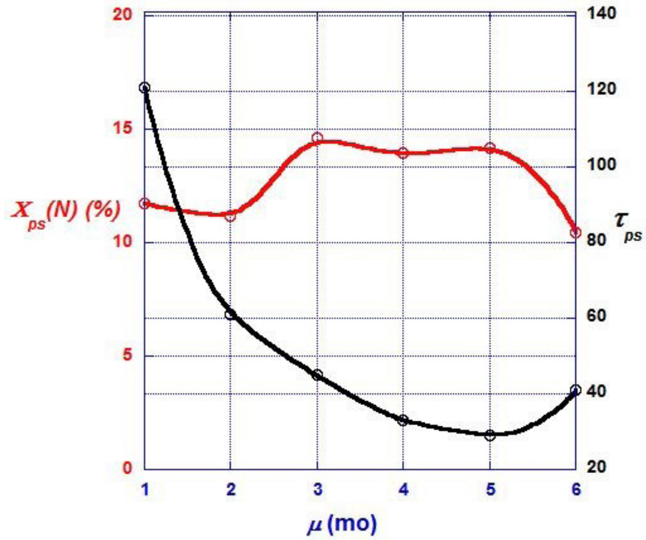
To find the best value of μ to use, we first look to maximize total return, $V(N) - 1$, or equivalently the cumulative annualized growth rate (CAGR) over the entire period, $\chi(N)$, where χ is defined as:

$$\chi(n) = \{[\exp((\log(V) / (n / 250))] - 1\} \times 100 \qquad \text{Equation 2}$$

(expressed as a percentage) and we have taken a trading year to consist of 250 trading days. Note that since $N = 2517$ here, Equation 2 evaluated at $n = N$ will slightly underestimate the true CAGR in the period of interest.

Figure 1 depicts $\chi_{ps}(N)$, as a function of the look back period, μ. Also shown is the number of trades made. It is observed that maximum CAGR approaches 15% at $\mu = 3$ months and that the performance is relatively insensitive to μ between three and five months. The number of trades decreases inversely with increasing μ in this period.

Figure 1. Cumulative annualized growth rate for the pair switching algorithm for the 10-year period ending 12/31/13 as a function of look back period. Also shown on the right ordinate axis is the total number of trades made for each value of μ.



Also of interest is the maximum draw down, defined as

$$\delta_{\max}(n) = \underset{n=1\to N}{Max}\left\{\left[\underset{i=1\to n}{Max}(V(i)) - V(n)\right] / \underset{i=1\to n}{Max}(V(i))\right\}$$

For the cases shown in Figure 1, and expressed as a percentage, $\delta_{\max}(N)$ was 18.8% uniformly over the range $2 \le \mu \le 5$ months; this value first occurred on 4/30/09.

The Ivy 5 Strategy

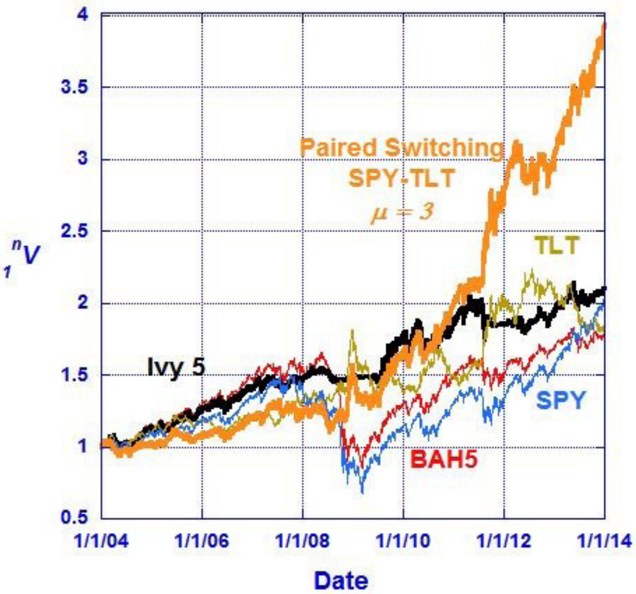
In applying the Ivy 5 strategy we utilize the ETFs suggested by Faber and Richardson (FR)[4] with one minor exception. There were no broad sector commodity ETFs available on 1/1/2004, the beginning of our 10-year study period. So, we have substituted the PIMCO Commodity Real Ret Strat Instl mutual fund (PCRIX) for the commodity ETF recommended by FR (DBC). The modified Ivy 5 trading rule is then:

Purchase equal amounts of the following ETFs/funds on day one if and only if the adjusted closing price exceeds the 10-month simple moving average (SMA): SPY (S&P 500), EFA (MSCI EAFE index), IEF (7–10 year treasuries), IYR (real estate), PCRIX (commodities). Otherwise the amounts meant for purchase are instead left in cash. Then, at the last day of this and each following month, repeat the procedure. Price fluctuations during the rest of the month(s) are ignored. Cash positions earn interest using IRX (CBOE index that measures the discount rate of the most recently auctioned 13-week U.S. Treasury Bill) as a surrogate. Again, nominal trading costs are included on all transactions.

Comparison of Paired Switching With the Ivy 5

Before proceeding, it will be convenient to slightly modify the nomenclature. We will redefine the normalized portfolio value on day $n > k$ as ${}^{n}_{k}V$ where $k \ge 1$ represents the day of purchase. Figure 2 then compares ${}^{n}_{1}V$ for the paired switching algorithm with that of the Ivy 5 portfolio. Also shown for reference are the buy-and-hold (BAH) values of SPY, TLT, and BAH5 (the portfolio consisting of initially equal dollar amounts of SPY, EFA, IEF, IYR, and PCRIX and in which no further trades are made).

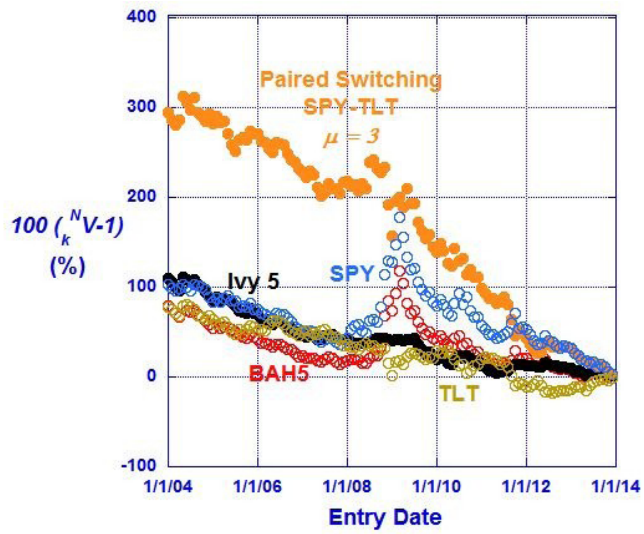
Figure 2. Portfolio value on day n,1 < *n* ≤ *N* = 2517, over the 10-year period n, beginning on 1/2/2004 and ending on 12/31/13



It is observed that ${}_1^NV$, the value on 12/31/13, for paired switching is roughly double that delivered by the Ivy 5 portfolio, although, for the first half of the 10-year period, ${}_1^nV$ for the former lags that of the latter by as much as 20%. The maximum draw down over the entire period for paired switching was 18.8% as against 14.6% for the Ivy 5. By contrast, ${}_1^N\delta_{\max}$ was 55.2% for SPY, 26.6% for TLT, and 48.4% for BAH5.

Figure 2 compared results for every date in the period given a single entry (purchase) date, namely 1/2/04, the first day of the period. More computationally intensive, but also of more interest, is what an investor might gain or lose at the end of the period for an investment made on any arbitrary date in the period. Figures 3–6 address this question. Figure 3 compares the total return as a function of entry date, ${}_k^NV - 1, 1 \le k \le N$, for paired switching with the Ivy 5 portfolio and with the three references in Figure3.

Figure 3. Total return on day *N*, the end day of the 10-year period beginning on 1/2/2004 and ending on 12/31/13 for entry date corresponding to day *k*, 1 ≤ *k* ≤ N = 2517.



The open and closed circles represent end-of-month entry dates, corresponding to the allowable entry dates with the paired switching and Ivy 5 rules discussed above; purchases made at other dates are assumed to be invested in cash, without interest, until the next end-of-month, at which point the appropriate purchase is made. It can be seen that the paired switching scheme produces higher total return at the end of the windowed period than the Ivy 5 independent of the entry date. And, although an investor purchasing SPY at the end of February 2009 and holding through 12/31/13 would have done almost as well as with paired switching, it is highly unlikely that he would have been able to identify the bottom of the market that produced this result. Figure 4 shows the CAGR in the same context, and with similar modified nomenclature, as in Figure 3. Over the entire set of entry dates the minimum, mean, and maximum values for paired switching are 14.4%, 20.4%, and 31.9%, respectively. Note that the CAGR values after 12/31/12 are suppressed for clarity because the results are highly volatile and not meaningful for $n / 250 \ll 1$ in Equation 2. The comparable CAGR minimum, mean, and maximum values for the Ivy 5 are 1.4%, 6.6%, and 9.8%, respectively. Figure 5 shows the maximum draw down for each of the cases in Figures 2–4 and exhibits the advantage of both paired switching and Ivy 5 schemes over buy-and-hold approaches.

Figure 4. CAGR on day N , the end day of the 10-year period beginning on 1/2/2004 and ending on 12/31/13 for entry date corresponding to day *k*, 1 ≤ *k* ≤ *N* = 2517

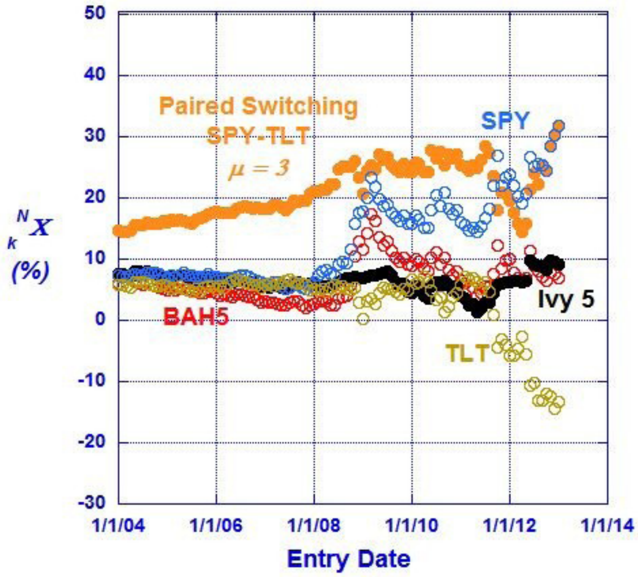
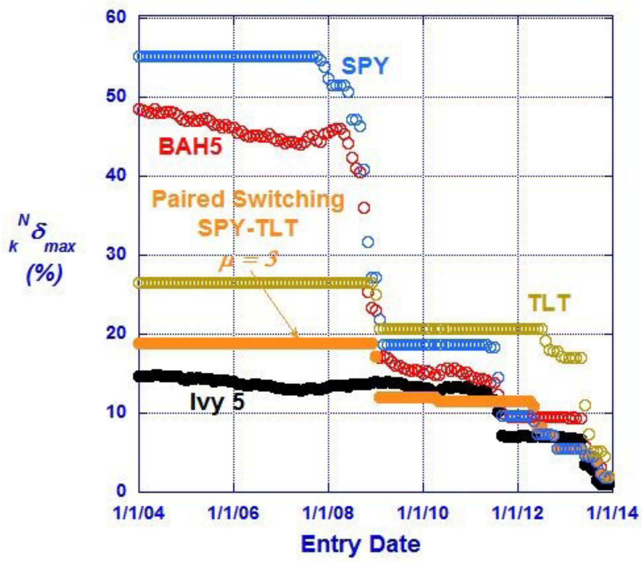
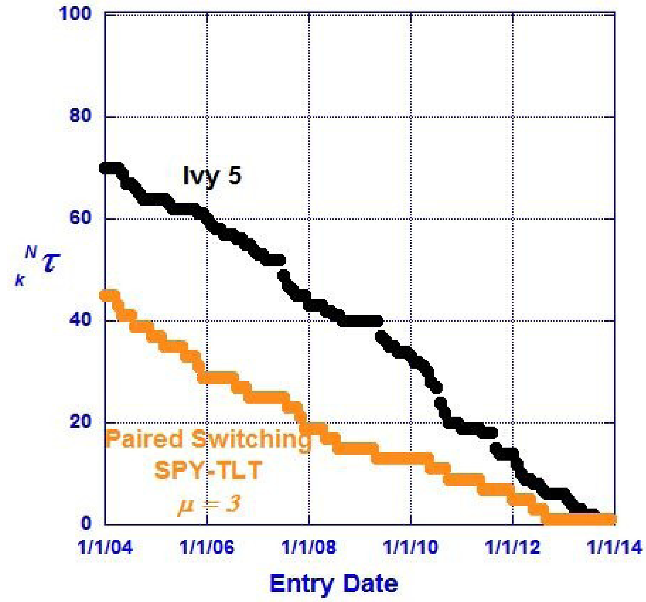


Figure 5. Maximum draw down on day *N*, the end day of the 10-year period beginning on 1/2/2004 and ending on 12/31/13 for entry date corresponding to day *k*, 1 ≤ *k* ≤ *N* = 2517



With neither timing scheme did the maximum draw down exceed 20%, independent of entry date but the Ivy 5 had smaller drawdowns for most entry dates. Finally, Figure 6 depicts the number of trades employed (each switch counts for two trades with paired switching) for the Ivy 5 and paired switching schemes. It is clear that the latter has the advantage regardless of entry date. As mentioned earlier, even though the explicit cost of electronic trading is now generally negligible, the cost of slippage (the difference between the adjusted closing price and the price actually obtained in a transaction) is not easily accounted for. Slippage is not a deterministic process and, while bounds may be established using Monte Carlo methods, this is beyond the scope of the present study.

Figure 6. Number of trades on day N , the end day of the 10-year period beginning on 1/2/2004 and ending on 12/31/13 for entry date corresponding to day *k*, 1 ≤ *k* ≤ *N* = 2517



Discussion

The results presented in the previous section would appear to show that the paired switching scheme has the advantage over the Ivy 5 unless draw down is the main concern, in which case the significantly increased return of the former would need to be balanced against its modest increase in risk. One question that arises, however, is the significance of these results in predicting future performance. For one thing, most of the ETFs involved in both schemes have been in existence only a short time so only a rather narrow 10-year period was considered. As mentioned earlier, this problem was dealt with by Faber[3] for the Ivy 5 by testing the algorithm with non-trade-able indices over a 35-year period. In their analysis of paired switching, Maewal and Scalaton[8] employed the statistical procedure devised by Henriksson and Merton[10] to evaluate the significance of their results. They also suggested a similarprocedure to that employed by Faber for the Ivy 5, in this case the use of surrogate mutual funds—VFINX for the S&P 500 and VUSTX for the treasury long bond. The former has been in existence since 1980 and latter since 1986. Figures 7–11 show the results of our applying the paired switching algorithm described in "The Paired Switching Strategy" with these two mutual funds over a 25-year period beginning on 1/4/1988 and terminating on 12/31/13. In this case, the number of trading days, N = 6966.

Figure 7. Portfolio value on day 1 < *n* ≤ *N*, over the 25-year period *n*, beginning on 1/4/1988 and ending on 12/31/13

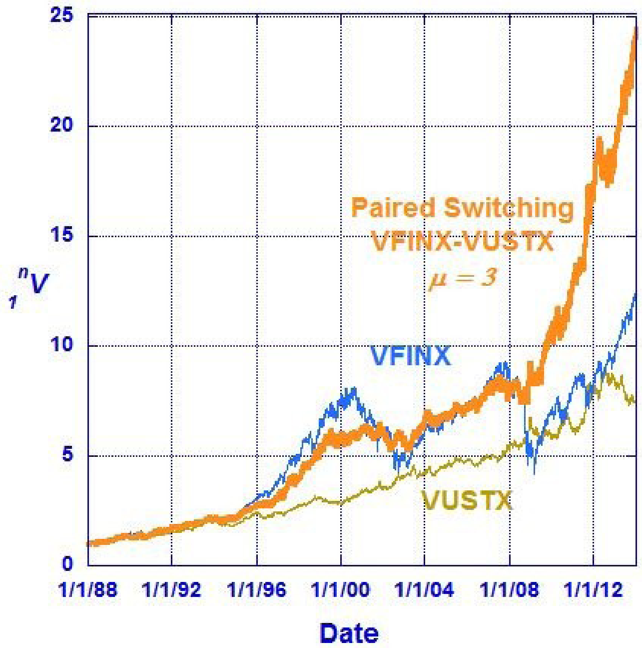


Figure 7 shows that the portfolio value at the end of the period with paired switching is double that obtained by buying and holding the S&P 500 index surrogate and, as will be seen below, this result was obtained with significantly less risk. In deriving this result the trading rule Equation 1 was applied even though, strictly speaking, extant short-term trading restrictions would have prohibited its use. Moreover, when trading mutual funds, the daily price is obtained only after the market closes so that Equation 1 would need to be modified such that an indicated trade at month's end would need to be made at the following day's close, which would also avoid any slippage.

As before, Figure 7 compares results for every date in the period given a single entry (purchase) date, in this case 1/4/1988, the first day of the period. Figures 8–11, by contrast, exhibit the results at the end of the period for an investment made on any arbitrary date in the period. Figure 8 shows the total return as a function of entry date, ${}^{N}_{k}V - 1, 1 \le k \le N$, for paired switching and with buy-and-hold of VFINX and VUSTX. The value of almost 2400% return over the 25-year period amounts to almost 95% average annual return, which substantially exceeds the 30% average over the 10-year period in Figure 3. However, note that the total return for paired switching is only double that for BAH of VFINX whereas, in Figure 3, the total return for paired switching over the 10-year period is three times that of SPY.

Figure 8. Total return on day *N*, the end day of the 25-year period beginning on 1/4/1988 and ending on 12/31/13 for entry date corresponding to day *k*, 1 ≤ *k* ≤ *N* = 6966

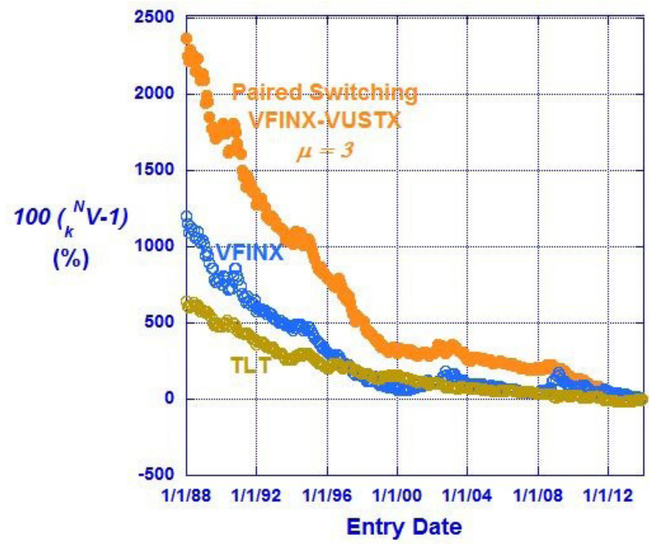


Figure 9. CAGR on day *N*, the end day of the 25-year period beginning on 1/2/1988 and ending on 12/31/13 for entry date corresponding to day *k*, 1 ≤ *k* ≤ *N* = 6966

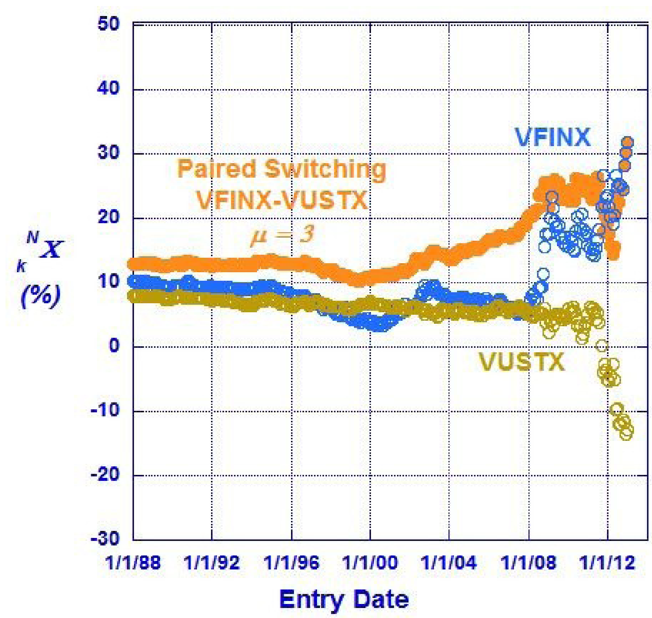


Figure 10. Maximum draw down on day *N*, the end day of the 25-year period beginning on 1/2/1988 and ending on 12/31/13 for entry date corresponding to day *k*, 1 ≤ *k* ≤ *N* = 6966

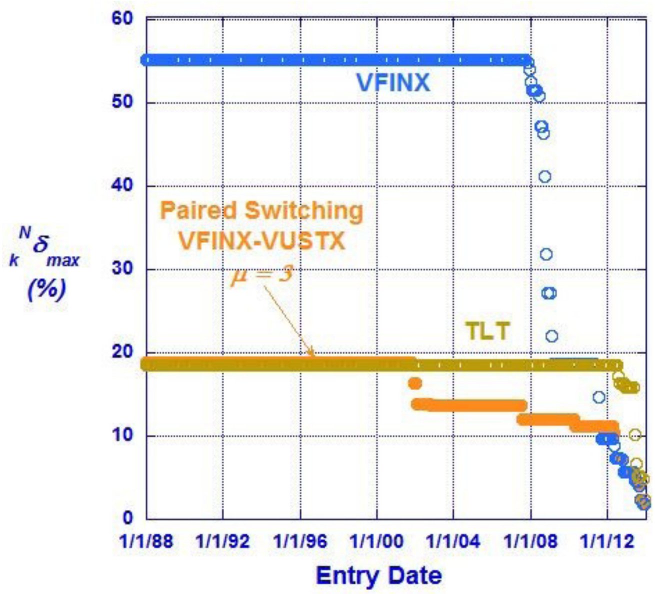
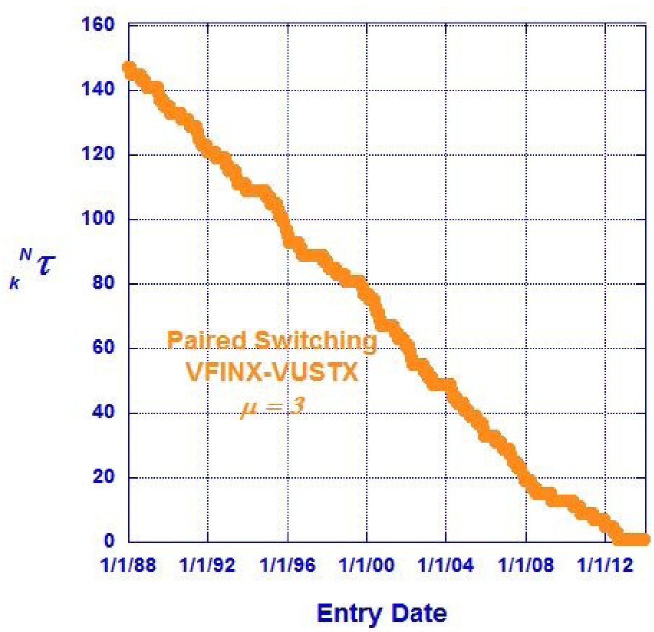


Figure 11. Number of trades on day *N*, the end day of the 25-year period beginning on 1/2/1988 and ending on 12/31/13 for entry date corresponding to day *k*, 1 ≤ *k* ≤ *N* = 6966



CAGR results are shown in Figure 9. Over the entire set of entry dates in the 25-year period the minimum, mean, and maximum values for paired switching are 10.2%, 15.2%, and 31.7%, respectively. These values are comparable to the values obtained with SPY and TLT in the 10-year period and shown in Figure 4. The maximum draw down numbers in the 25-year period, shown in Figure 10, are also similar to those for the 10-year period in Figure 5 and the number of trades shown in Figure 11, a little less than six per year on average, compares with the 4 ½ average number obtained from Figure 6.

Finally, we should comment on the evaluation period, κ. In this study we chose to evaluate the paired switching portfolio at the end of each month, in accordance with the rule used for the Ivy 5. However, as mentioned earlier, Maewal and Scalaton[8] only evaluated the possibility of switch every three months, corresponding to the 3-month look back period. Moreover, Cohn[9] employed an evaluation period of one day, together with a look back period of 84 days (it can be shown that, with a one day evaluation period, the optimal performance has a steep maximum about the 84-day look back period). Table 1 summarizes the performance for these three cases over the 10-year period ending on 12/31/13.

Table 1. Total return, CAGR, maximum drawdown, and total number of trades for three different paired switching parameter sets for the 10-year period beginning on 1/2/2004 and ending on 12/31/13 (*N* = 2517)

	100 (${}_1^N V$ - 1) %	(${}_1^N\chi$) %	(${}_1^N\delta_{max}$)%	${}_1^N\tau$
κ = 1 mo, μ = 3mo	294.1	14.6	18.9	45
κ = 3 mo, μ = 3mo	193.9	11.3	24.1	41
κ = 1 day, μ = 84 days	327.8	15.5	17.1	189

It can be seen that with κ = 3 months, the number of trades is only slightly less than with κ = 1 month, but the performance suffers significantly. Conversely if paired switching is evaluated on a daily basis, with a look back period of 84 days, a roughly 1% increase in CAGR is obtained, together with a small decrease in maximum draw down. However, in this case, the number of trades increases by a factor of four so that slippage becomes a significant factor.

Conclusion

Paired switching refers to investing in one of a pair of negatively correlated assets and periodic switching of the position on the basis of the relative performance of the two. The specific pair examined in this study is the S&P 500 index and the index for U.S. treasury bonds with 20 or more years duration. It was shown that using mutual fund surrogates, VFINX for the former and VUSTX for the latter, and switching between the two at the end of each month based on whichever had the higher return over the past three months, a total return of almost 2400% could have been achieved over a period of 25 years ending on 12/31/13, double that obtained by buying and holding VFINX alone in this period. Moreover, this result would have been obtained with significantly less risk; draw down was only a third that with buy-and-hold. Unfortunately, short-term trading restrictions on these mutual funds, still in place, would have made it difficult, if not impossible, for the average investor to use this method. With the advent of exchange traded funds, however, the game has changed. ETFs are readily available that track the S&P 500 index (SPY) and the long bond (TLT). The low electronic trading cost coupled with the huge daily volumes provide the liquidity with which slippage can be minimized. Using the same paired switching rule just described it was shown that the total return over the 10-year period ending on 12/31/13 was almost 300%, three times higher than that obtained by buying and holding SPY alone, and also three times higher than that obtained with the popular Ivy 5 method described in "The Ivy 5 Strategy" above. And, as with the mutual funds over the 25-year period, the draw down with paired switching was only a third that with buy-and-hold of SPY. The number of trades with paired switching over the 10-year period was 45, compared with 70 for the Ivy 5, although the latter had slightly lower maximum draw down (14.6% versus 18.8% for paired switching).

Notes

[1] Lewis A. Glenn is a Founding Partner and Chief Scientific Officer of Creative Solutions Associates LLC, a private investment and wealth management group.

[2] Malkiel, B. G., "A Random Walk Down Wall Street" (2007), W. W. Norton & Company

[3] Faber, Mebane T., A Quantitative Approach to Tactical Asset Allocation (February 1, 2013). *The Journal of Wealth Management,* Spring 2007. Available at SSRN: http://ssrn.com/abstract=962461

[4] Faber, M. T. and Richardson, E. W., The Ivy Portfolio—How to Invest Like the Top Endowments and Avoid Bear Markets, John Wily & Sons, 2009.

[5] Glenn, L. A., Market Timing with Volatility, Active Trader, 10, No. 7, July 2009, pp. 28-31; see also Beat the Market—A Strategy for Conservative Investors (December 12, 2008). Available at SSRN: http://ssrn.com/abstract=1315533

[6] Glenn, L. A., Market Timing using Exchange Traded Funds, The Technical Analyst, July-Sept. 2010, pp.16-24. Available at SSRN: http://ssrn.com/abstract=1591969; see also Playing Both Sides, Active Trader, 11, No. 9, September 2010, pp. 44-49

[7] Glenn, L. A., Adaptive Market Timing with ETFs (December 28, 2010). Available at SSRN: http://ssrn.com/abstract=1732010

[8] Maewal, Akhilesh and Scalaton, Joel B., Paired-Switching for Tactical Portfolio Allocation (August 22, 2011). Available at SSRN: http://ssrn.com/abstract=1917044

[9] Cohn, Marc, Return Like a Stock, Risk Like a Bond: 15.5% CAGR with 17% Drawdown, (February 23, 2014), Available at http://seekingalpha.com/article/2041703-return-like-a-stock-risk-like-a-bond-15_5- percent-cagr-with-17-percent-drawdown?ifp=0.

[10] Henriksson, R. D. and Merton, R. C., On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills, *J. Business,* 54, No. 4, October 1981, pp. 513-533.

How the Average Investor Can Use Technical Analysis for Stock Profits: An In-Depth Work on Stock Market Technical Analysis, Mob Psychology, and Fundamentals *by James Dines*

Reviewed by Regina Meani, CFTe

Amazon describes it as James Dines' famous treatise on technical analysis for the stock market and advises that there are no reviews. On the *Dines' Letter* website, there is a quote from a *Barron's Magazine* reviewer, but I fear this was back in the 1970s and no longer readily available. I reached onto my bookshelves and pulled out my treasured tome, thinking it was time for a 21st century review. First published in 1972 after taking James Dines 11 years to write, he set about publishing it himself through the Dines Chart Corporation, and it was reprinted in 1973 and 1974. Not only was he a pioneer in his thinking on stock market analysis but also in publishing his own work nearly 50 years ago. There is a massive 599 pages that have been written to involve both the beginner and the more advanced. *The London Financial Times* commented that "Mr Dines has done for Technical Analysis what Graham & Dodd has done for Fundamental Analysis."

Part One deals with Mass Market Psychology, and one is immediately confronted with the first topic: *Sex and the secret desire to lose.* While some parts of this section may be questioned by modern society's correctness, it remains an interesting interpretation of people's attitudes to the share market. We are also introduced to "Pigeon", who features throughout and I must admit has helped me out in many of my presentations. Pigeon adds humour and allows us to connect with the text as we empathize with Pigeon's ongoing predicaments.

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Throughout, Dines tempers his work with sage advice. By page 123, we have reached Part Two—Technical Analysis. *To like everyone is to be indifferent to everyone. Same with charts, you must choose. It is the act of choosing which is the business of this book.*[3]

In a clear and precise manner, Dines explains the different types of charts in his section on "How to Chart". He deals with Point and Figure, the arithmetic bar, and the semi-log bar and advises that we should use all three. He states that "*Each measures different technical factors: price change and volume in time, percentage of price change and volume in time and price change alone. All reveal different facets of a stock's personality-in-motion. While the methods of analysis are homologous. The conclusions reached are often surprisingly different.*"[4] It is a shame that we do not have his interpretation of candlesticks, but I believe that it wasn't until the 1990s that they became popular in the western world. Dines uses Point and Figure charts for most of his prolific examples, and he uses his own particular style. Most of us are familiar with the "X" and "O" technique, but Dines just uses crosses and refers to them as "Cross Charts". The interpretation is the same; they just look slightly different and are a little harder to manually construct.

Dines manages to bring reality to his text by using excerpts from the *Dines Letter.* In one interesting piece, he deals with the criticisms of the Dow Jones Industrial Average as to its value as a market indicator, which remains a relevant topic to this day. For his argument, he uses quotes from the *New York Times* and from Arthur Merrill's *Behavior of Prices on Wall Street.* The joint conclusion from the comparison to the broader indices was that "*The price action in the two averages has been amazingly similar. But this nonetheless does not prove the DJI is always representative of the market.*"[5]

There are detailed descriptions of chart patterns, moving averages, and both financial and technical indicators and, most importantly, how to use these to make profits. I continue to use many of his techniques, particularly those for moving averages, finding that along with his behavioural studies, they have stood the test of time and the changing market scene.

To continue a more detailed review, and do justice to Dines' work, would perhaps take most of the *Journal* pages, and this would be without attempting to critique his section on Fundamental Analysis. Many have referred to Dines' book as a "classic" and to the man as a "legend", and both no doubt have merit for maintaining positions of excellence for 50 years or more.

One of my more memorable moments was attending a talk by Dines when he visited Australia. I approached him, clutching my copy, and I believe that he was both pleased and surprised. I'm not sure, but my guess was that he was surprised it had made it to Australia due to its limited publication. I might also guess that my signed copy would be worth more than the current price of AUD$1,365 (US$994) and perhaps it could be said that it has proved one of my better investments.

Notes

1 *The Dines Letter*—Mr. Dines' Bio: https://www.dinesletter.com/bio.html

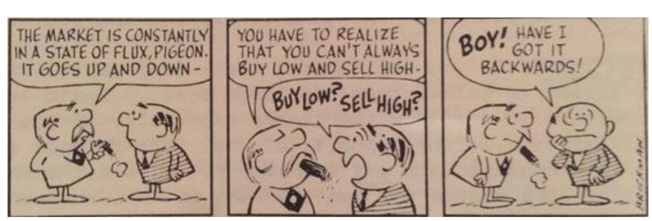
2 Dines, J, How the Average Investor Can Use Technical Analysis for Stock Profits, Dine Chart Corporation, USA, 1972, p. 1

3 ibid, p. 123

4 Ibid, p. 323

5 Ibid, p. 345

6 Ibid, p. 138



6

Author Profiles

Ron Albert Marcelino Acoba, CFTe, CMT, MFTA

Ron Albert Marcelino Acoba, CFTe, CMT, MFTA, is the chief investment strategist and co-founder of Trading Edge Consultancy, a third-party research provider for banks and brokerage firms in the Philippines. Ron has more than 15 years of experience in the investment industry. He used to be an equity dealer and forex trader for Credit Suisse Philippines, as well as an equity fund manager and chief equity dealer for BPI Asset Management and Trust Group, where he personally managed US$500 million in discretionary funds. Earlier in his career, he worked as a forex analyst and trader for BabyPips.com, LLC. Ron received his undergraduate degree in economics from the Ateneo de Manila University. He also holds an MBA from the University of the Philippines.

Momen Atef El Shayal, CFTe, MFTA

Momen Atef El Shayal, CFTe, MFTA, is the head of the technical analysis department at SIGMA Securities Brokerage. He has almost 10 years of experience in the capital markets. He earned a B.Sc. in commerce in 2008 and acquired his CFTe in 2013. Momen is a member of the Egyptian Society of Technical Analysts (ESTA). He started his career in Jazira Capital as a senior technical analyst in 2011 and was promoted to chief technical analyst in 2013, serving both asset management and brokerage divisions. In 2016, he joined the SIGMA Securities Brokerage team, where he is responsible for technical analysis products for individual and institutional clients covering the MENA and U.S. markets.

Mohamed Fawzy ElSayed Ali AbdAlla, CETA, CFTe, MFTA

Mohamed Fawzy ElSayed Ali AbdAlla, CETA, CFTe, MFTA, is a urology consultant in the National Institute of Urology and Nephrology in Egypt. He is also deeply interested and involved in the analysis of financial markets. He has five years of experience as an independent investment strategist handling his family portfolio.

As a private investor, Mohamed grew to believe that achieving continuous portfolio growth is obtained by creating and improving a reliable money management trading system, which can only be reached through integration of two main success tools: technical analysis as the only signal provider and, more importantly, statistics and programming languages for better diversification, allocation, risk management, and performance analysis.

Lewis A. Glenn, Ph.D.

Lewis A. Glenn, Ph.D., is a founding partner and chief scientific officer at Creative Solutions Partners Associates LLC, a private investment and wealth management group with offices in the San Francisco Bay Area and Lausanne, Switzerland. In a previous life Lewis led the Computational Physics Group in the Earth Sciences Division at the Lawrence Livermore National Laboratory in Livermore, California.

Yukitoshi Higashino, MFTA

Yukitoshi Higashino, MFTA, is chief technical strategist of the equity research team at DZH Financial Research, an investment information firm located in Tokyo as Shanghai DZH Limited group. He leads the development of technical strategies for client securities firms dealing in futures, ETFs, and CFDs. His main responsibilities range from analysis of major indices of the Asian and world markets and can extend to even individual stocks. Prior to this, he was a stock lending trader for foreign securities houses and a treasury stock trader for Mizuho Trust Bank. He was also an equity trader and a market analyst at a securities firm. Yukitoshi is director of the Nippon Technical Analysts Association (NTAA). He is also a member of the Financial Planners Association of Japan (CFP). He made presentations at the IFTA conferences in Vancouver, Lugano, Berlin, and Cairo.

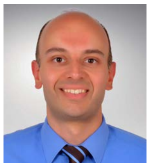
Mohamed M. Khedr, CFTe, MFTA

Mohamed M. Khedr, CFTe, MFTA, has been working as a senior technical analyst at Prime Securities since 2014. He has over 12 years of experience in the Egyptian capital market. Before joining Prime Securities, he was a senior account manager at NAEEM Holding Co. Prior to that, he worked as a senior technical analyst at Tycoon Securities. Mohamed started his career at Mirage Brokerage Co. in the customer service department. He then became a broker, a research technical analyst, and finally the head of the technical analysis department. He also created a new department (call center) to answer clients' technical questions. Mohamed has a bachelor's degree in accounting from the Faculty of Commerce at Cairo University. He has a brokerage license from ECMA (Egyptian Capital Market Association) and is a CPM holder (Certified Portfolio Manager) from EIMA (Egyptian Investment Management Association).

Kevin Luo

Profile not available.

Mohamed Ashraf Mahfouz, CETA, CFTe, MFTA



Mohamed Ashraf Mahfouz, CETA, CFTe, MFTA, is chief technical analyst for Commercial International Brokerage Company (CIBC), one of Egypt's top-ranked brokerage houses. CIBC is the securities brokerage division of CI-Capital, the premier investment bank in Egypt, with market-leading leasing, microfinance, investment banking, securities brokerage, asset management, and research franchises. Prior to this he was the head of the technical analysis desk for Dynamic Securities Brokerage Company, a CI-Capital member.

He served as a board member and vice president for the Middle East and Africa region of IFTA from 2010 until 2016. During this period, he implemented MOU agreements between IFTA and the United Arab Emirates Securities and Commodities Authority (ESCA) and between IFTA and the Capital Market Authority in Sultanate Oman (CMA), and he was responsible for translating the CFTe bank of questions into the Arabic language. He also served as a board member in the Egyptian Society of Technical Analysts (ESTA) from 2011 until 2015, and he has been a key education committee member in ESTA since 2007. Mohamed has taught technical analysis at many financial institutions and universities for more than 14 years. He graduated from the Faculty of Economics and Political Sciences, Cairo University.

Regina Meani, CFTe

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

Przemysław Smoliński, MFTA

A 20-year enthusiast of technical analysis and trading, both professionally and as a hobby, Przemysław Smoliński, MFTA, got interested in the stock market in the last year of primary school and still has been fascinated by drawing lines, designing, and coding trading strategies. From 2000–2006, he worked at mBank Securities, and since 2006, he has been working as an analyst in the brokerage house of the largest bank in Poland, PKO BP—first in the Research Department and currently at the Technical Analysis and Investment Advisory Department. Invariably, since 2012, he has been considered one of the best technical analysts in the newspaper's "Parkiet" ranking, and his analytical products three times got to the short list of finalists in the competition organized by the British magazine *The Technical Analyst.* Nowadays, Przemysław is mainly focused on combining classical technical analysis and statistical tools with the possibilities offered by automated trading.

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International Federation of Technical Analysts
1300 Piccard Drive, Suite LL 14
Rockville, MD 20850 USA
Phone: +1 (240) 404-6508
Fax: +1 (301) 990-9771
Email: admin@ifta.org | Web: www.ifta.org

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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, Arabic, and Chinese; 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, Arabic, and Chinese, 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/.

To Register

Please visit our website at http://www.ifta.org/certifications/registration/ for registration details.

Cost

IFTA Member Colleagues	Non-Members
CFTe I $550 US	CFTe I $850 US
CFTe II $850* US	CFTe II $1,150* US

*Additional Fees (CFTe II only):
$100 US applies for non-IFTA proctored exam locations

IFTA Master of Financial Technical Analysis

Master of Financial Technical Analysis (MFTA) Program

IFTA's Master of Financial Technical Analysis (MFTA) represents the highest professional achievement in the technical analysis community, worldwide. Achieving this level of certification requires you to submit an original body of research in the discipline of international technical analysis, which should be of practical application.

Examinations

In order to complete the MFTA and receive your Diploma, you must write a research paper of no less than three thousand, and no more than five thousand, words. Charts, Figures and Tables may be presented in addition.

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

$950 US (IFTA Member Colleagues);
$1,200 US (Non-Members)

International Federation of Technical Analysts