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You can't predict the future, but you can prepare for it.

—Maurice Blondel

(French Philosopher, 1861-1949)

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Dato’ Dr. Nazri Khan is an economist graduate of the University of Manchester with international stock market experience, conducting over 1000 retail investment functions in Malaysia and overseas.

He was formerly the Vice President, Head of Retail Research in Affin Hwang Investment Bank Bhd and is a Full Member Of The UK Society Of Technical Analyst. He has been in stock market industry for twenty years and is currently the Chairman of Malaysian Association Of Technical Analyst. Prior to Affin, he was the Head of Research in MIMB Investment Bank.

IFTA Journal

MFTA Papers

Articles

Book Review

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Balance professional development and your personal life with our new Home Study Course©

In February 2018 the STA launched the new Home Study Course, HSC 2©. This is an exciting upgrade to the hugely successful HSC© which has been a number of years in development. The STA's aim was simple - to give you the best product on the technical analysis market, not just in course content or the number of experts involved in its development, but also with the administrative and continuous student support you receive.

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Letter From the Editor

By Aurélia Gerber, MBA, CFA, MFTA

Dear IFTA Colleagues and Friends:

This year's 31th conference in Kuala Lumpur and the *IFTA Journal*—with the theme "Navigating Through Time & Volatility"—are about exploring and tinkering with ideas on how trading and investing have evolved, from the perspective of "time." The theme provides an overview on various techniques, methodologies, ideas, systematic trading systems, and adaptation on momentum investing. Technical analysis continues to progress, being infused with new ideas and techniques. This is what makes technical analysis such a fascinating topic.

While technical analysis covers a broad range of theories, techniques, and tools, those might be of little use without method. Technical analysis is a method of forecasting the direction of financial market prices through the evaluation of historic price and, where available, volume data. A basic premise of the technical approach is that market action discounts everything: all that is known, or can be known, is "in the price," and that price movements are not entirely random—they move in trend, and history has a tendency to repeat itself. A wide range of techniques might be applied to this assessment of price action, including the study of repetitive patterns on charts, mathematical calculations, and statistical tools.

The *IFTA Journal* is—through its global distribution to professionals in the field within member societies from 27 countries—one of the most important forums for publishing leading work in technical analysis. The *IFTA Journal* is composed of three sections: in the first section, we have published four Master of Financial Technical Analysis (MFTA) research submissions. This body of work offers fresh and multiple ways of looking at the behavior of markets and is testament to the high standing of the MFTA designation. Three MFTA papers deal with indicators to define trends and momentum, and one explores Empirical Mode Decomposition applied to financial time series as oscillators.

Technical analysis continues to progress, being infused with new ideas and techniques.

In the second section, articles were submitted by IFTA colleagues. One article was submitted by The Nippon Technical Analysts Association (NTAA) on the SKURT indicator. There is an academic paper on model-based geometric pattern recognition; one on the great Dow Theory, one of the forefathers of technical analysis; and a paper focusing on day trading returns across volatility states.

In the third section, we are very thankful to have had the support of our book proposal reviewer, Regina Meani, on David Keller's *Breakthroughs in Technical Analysis: New Thinking From the World's Top Minds.*

This variety of content continues to provide unique opportunities for readers to advance their knowledge and understanding of the the practice of technical analysis and keep abreast of new research and ideas. This year's Journal was produced by a returning team for IFTA. I would like to thank Rolf Wetzer and Regina Meani for their help in editing this *Journal.* These articles were also peer reviewed by a team of reviewers guaranteeing the quality of the *IFTA Journal.*

We are also able to create this timely and unique journal because of the intellect and generosity of time and materials from the authors. The *IFTA Journal* continues to attract submissions from authors around the world, and we sincerely appreciate the efforts of all who offer to share their research and ideas with us and our readers.

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

Linear Momentum and Performance Indicators

By Akram El Sherbini, MFTA, CFTe, CETA

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Abstract

"Momentum is not the same as velocity. A lot of words are used in physics, and they all have precise meanings in physics, although they may not have such precise meanings in everyday language. Momentum is an example, and we must define it precisely." (Feynman, 1965).

Since momentum indicators have been introduced to the field of technical analysis, many analysts use momentum when they refer to price acceleration. As the study of price movement is the main concern of technical analysts, the laws of motion, including Newton's second law, are applied to prices to clarify the difference between price acceleration, momentum and force. This paper will attempt to adjust the price momentum and force concepts introduced by Welles Wilder and Alexander Elder, respectively. By introducing the concept of linear momentum, new indicators will emerge to dissect the market performance into six main elements: market's force, pressure, strength, power, intensity, and dynamic strength. This will lead to a deeper insight about market action. The leading performance indicators can be used simultaneously to identify price turning points and filter irrelevant divergences. The linear momentum and the new performance indicators should make a significant change in categorizing several indicators in technical analysis.

Introduction

Momentum in Technical Analysis

"One of the most useful concepts in technical trading is that of momentum; yet, for many traders, momentum is also one of the hardest concepts to understand. Momentum can be thought of as acceleration and deceleration" (Wilder, 1978). The formula of momentum used in technical analysis is:

$$M = C - C_n$$

Where C is the latest closing price and C_n is the closing price n days ago.

The previous formula describes only the price displacement. It does not refer to price velocity and price acceleration. As we will see later in this paper, the momentum definition is different than the one stated by Welles Wilder.

Force Index in Technical Analysis

The Force Index *FI* is an oscillator developed by Alexander Elder that measures the force of buyers during rallies and of sellers during declines. "It combines three essential pieces of market information—the direction of price change, its extent, and trading volume" (Elder, 1993). The formula is described as:

$$FI = Volume_{today} \, (Close_{today} - Close_{yesterday})$$

The previous formula describes the linear momentum of buyers and sellers. It does not refer to the force behind it. Yet, there is a relation between the linear momentum and the linear force behind the motion of prices. In this paper, the terms *momentum* and *linear momentum* will have the same meaning, as well as *force* and *linear force.*

Mass and Volumes

"Mass is an inherent property of an object and is independent of the object's surroundings and of the method used to measure it. Also, mass is a scalar quantity and thus obeys the rules of ordinary arithmetic. That is, several masses can be combined in simple numerical fashion" (Serway, 2004). In classical physics, the mass *m* of an object is independent of its velocity. On another note, if the mass of an object is equal to zero, then such an object simply does not exist.

Similarly, volumes are scalar quantities that are independent of price direction and velocity. For example, the today's price can increase by any amount whether the volume of today *V* is 100 or 1,000 shares. Moreover, if the number of shares at any day is equal to zero, the price will not exist during that day. On a price-time chart, the price acts like a body constituted from building blocks of shares. A point that changes its position with time represents the price body.

Figure 1a. A Body With Mass *m* Moving on a Position-Time Chart

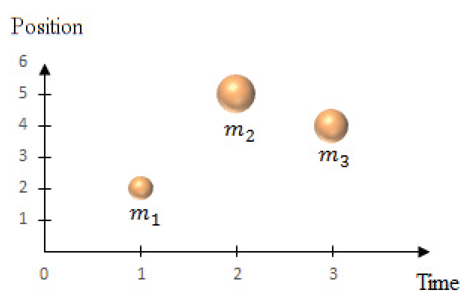
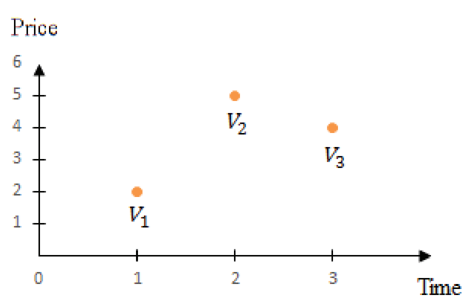


Figure 1b. Price Body With Volume *V* Moving on a Price-Time Chart



Derivatives and Integrals

Derivatives and integrals are fundamental tools of calculus. Differential calculus is concerned with the study of the rates at which quantities change. Integral calculus is concerned with the study of joining or integrating quantities together to find how much there is. It is a way of adding slices to find the whole. Integration is the reverse process of differentiation; hence, integrals are also called anti-derivatives. In this paper, some notations are used for derivatives and integrals. For example,

$$y = \frac{dx}{dt} \qquad x = \int y\,dt$$

The first equation means that *y* is equal to the derivative or the change in x *dx* with respect to time *dt.* The second equation refers to *x* is equal to the integral ∫ of *y* with respect to time *dt.*

$$x \xrightarrow{\text{by differentiation yields}} y$$

$$y \xrightarrow{\text{by integration yields}} x$$

In this paper, we are going to use the integration technique to reduce the sensitivity of performance indicators instead of increasing their moving average period.

Price Velocity and Acceleration

In scientific context, the average velocity $\bar{v}$ of a particle is defined as the particle's displacement Δx with respect to a certain time interval Δt.

$$\bar{v} = \frac{\Delta x}{\Delta t} = \frac{x_{final} - x_{initial}}{t_{final} - t_{initial}}$$

In figure 1b, let us consider the final time to be the third day on the chart and the initial time to be the second day. Then, the price average velocity $\bar{v}$ is

$$\bar{v} = \frac{\Delta x}{\Delta t} = \frac{4-5}{3-2} = -1 \text{ point/day}$$

The average acceleration $\bar{a}$ of a particle is defined as the particle's change in velocity Δv with respect to a certain time interval Δt.

$$\bar{a} = \frac{\Delta v}{\Delta t} = \frac{v_{final} - v_{initial}}{t_{final} - t_{initial}}$$

In figure 1b, let us consider Δt is equal to one. Then, the price average acceleration at day 3 is

$$\bar{a} = \frac{\left(\frac{4-5}{3-2}\right) - \left(\frac{5-2}{2-1}\right)}{(3-2)} = -4 \text{ points/day}^2$$

From the previous examples, the value of price velocity is different from price acceleration at the third day. In this paper, the terms *average velocity* and *velocity* will have the same meaning as well as *average acceleration* and acce*leration.* Going back to the formula of momentum in technical analysis, the right part ($C - C_n$) actually refers to price displacement. In addition, the price velocity is expressed by

$$v = \frac{C - C_n}{n}$$

The price acceleration is expressed by

$$a = \frac{(C - C_n) - (C_n - C_{2n})}{n^2}$$

Where C is the latest closing price, C_n is the closing price n days ago. In this paper, we are frequently going to use the price acceleration of today, which is expressed by

$$a_t = (C - C_y) - (C_y - C_{by})$$

Where C_y is yesterday's closing price and C_{by} is before yesterday's closing price. To simplify, the previous equation can be written as

$$a_t = (C - 2C_y + C_{by})$$

Linear Momentum

The linear momentum *p* of a particle having a mass *m* and moving with a velocity *v* is defined to be the product of the mass and velocity: *p= mv.* Earlier, Isaac Newton called momentum the quantity of motion. This is a more precise description than our present day word momentum, which is the Latin word for movement. As defined by Newton, "The quantity of motion is the measure of the same, arising from the velocity and quantity of matter conjunctly" (Newton, 1846). The mass or "the quantity of matter is the measure of the same, arising from its density and bulk conjunctly" (Newton, 1846). Therefore, the momentum of an object cannot be separated from its mass. Eventually, we cannot calculate price momentum while ignoring the mass of the price body — volume.

From its definition, momentum differentiates between light and heavy bodies moving at the same velocity. The price linear momentum is the product of volume and price velocity

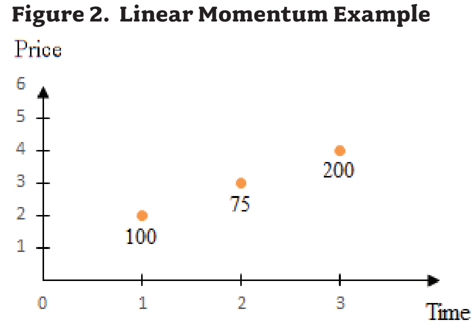
$$M = V.\frac{(C - C_n)}{n}$$

Where V is latest volume, C is the latest closing price and C_n is the closing price n days ago. One-day momentum is

$$M_{(1)} = V_{today}.(C_{today} - C_{yesterday})$$

Where n is equal to one.

Figure 2. Linear Momentum Example



In Figure 2, according to the Welles Wilder definition, the one-day momentum is the same for day 2 and day 3. By the new definition, momentum at the third day is greater than the second day. Table 1 shows the difference between Wilder's momentum and the linear momentum.

Table 1. One-Day Wilder's Momentum vs. One-Day Linear Momentum

Day	C	V	Wilder's Momentum	Linear Momentum
1	2.00	100	2	200
2	3.00	75	1	75
3	4.00	200	1	200

Performance Indicators

Performance indicators are derived from the linear momentum concept.

Table 2. Performance and Integral Performance Indicators

Performance Indicators	Integral Performance Indicators
Force	Integral Force *Linear Momentum*
Pressure	Integral Pressure
Strength	Integral Strength
Power	Integral Power
Intensity	Integral Intensity
Dynamic Strength	Integral Dynamic Strength

The performance indicators are leading to their integral performance indicators peers. As shown in Figure 3, buy signals are generated when the indicator's line or histogram moves above the zero line to turn positive. Sell signals are generated when the indicator's line or histogram moves below the zero line to turn negative.

Figure 3. Signals of Integral Performance Indicators

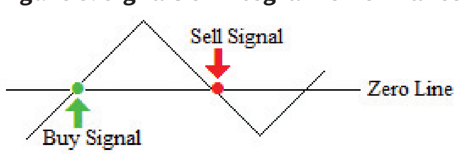
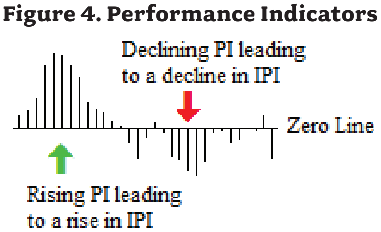


Figure 4. Performance Indicators Representation



As shown in Figures 3 and 4, the integral performance indicators are represented by a line moving around the zero level, while the performance indicators are represented by histogram.

Force Concept

According to the second law of Newton, the motion of an object is changed by forces *F* in the following way. The time rate of change of a quantity called momentum *p* is proportional to the force. Hence, F= dp/dt. In other words, the force acting on an object is equivalent to its change in momentum with respect to time. We can rewrite the previous equation as F= m.(d*v*/dt). Since the acceleration *a* of the object is the change in its velocity with respect to time *dv/dt,* then F= m.a

Linear Force Index and Integral Force Index

The linear force index *LFI* measures the force of buyers and sellers during rallies and declines, respectively. It combines two important pieces of market information—the price acceleration and volumes. The LFI is a short-term indicator, while its value of today is expressed by

$$LFI_{today} = V_{today}.\text{Price Acceleration}_{today}$$

$$LFI_{today} = V.\left(C - 2C_y + C_{by}\right)$$

Where V is the latest volume, C is the latest closing price; C_y is yesterday's closing price, and C_{by} is before yesterday's closing price. To reduce the sensitivity of the LFI, we add a 14-day exponential moving average to the price acceleration part so that

$$LFI_{today} = V.EMA_{14}\left(C - 2C_y + C_{by}\right)$$

By re-smoothing the previous formula, the LFI is

$$LFI = EMA_{14} \text{ of } LFI_{today}$$

Figure 5. Daily Values of Dow Jones Industrial Average (.DJI)

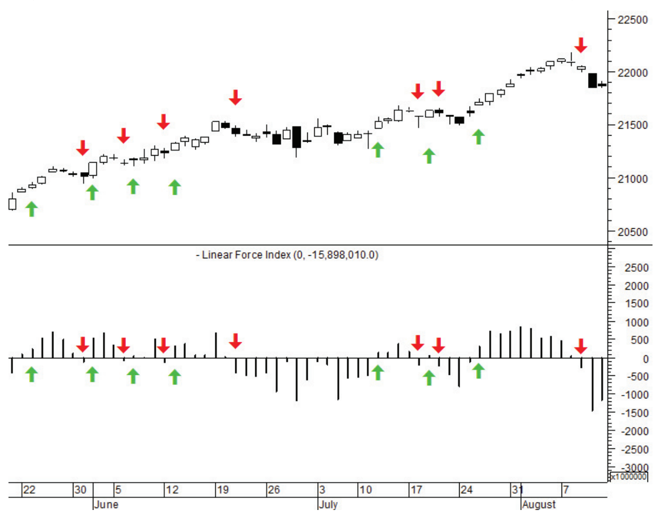


Figure 5 shows the buy and sell signals of the linear force index. Several false signal *whipsaws* were triggered due to the LFI's high sensitivity appearing from the price acceleration part. All performance indicators are sensitive enough to generate many whipsaws. Therefore, their integrals are used instead to preserve the concept behind them.

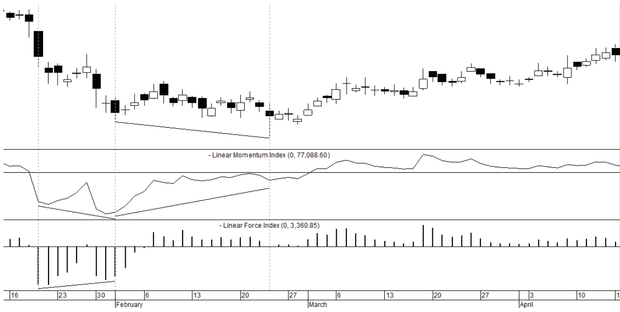
The integral force index *IFI* is introduced as an alternative method to smooth the linear force index. By applying the integration technique to the price force, this will yield price momentum. As mentioned earlier, the second law of Newton describes the force as the change in momentum *p* with respect to time. F=dp/dt. Conversely, the integration of force with respect to time is nothing else than momentum.

$$\text{Momentum} = \int \text{Force dt}$$

Consequently, the IFI of today's value is the product of today's volume and today's price velocity, where $IFI_{today} = V.(C - C_y)$;

alternatively, the linear momentum index *LMI* is expressed by $EMA_{14}[V.(C-C_y)]$. Therefore, Elder's force index describes the market momentum and not force.

Figure 6. Egyptian Stock Exchange — Daily Values of Six October Development (OCDI.CA)



In Figure 6, a positive divergence occurred between the LFI and LMI, leading the latter to rise in February 2016. Successively, a positive divergence between the LMI and prices has led the price momentum to increase from March 2016.

Figure 7. LMI and LFI Signals — Daily Values of Six October Development (OCDI.CA)

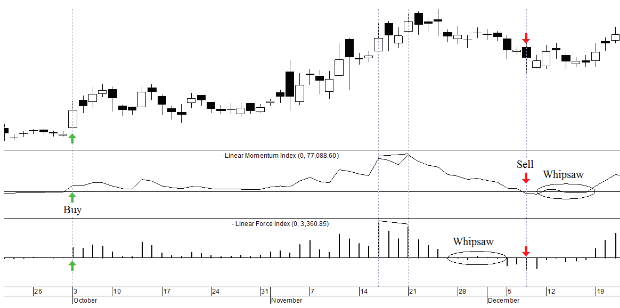


Figure 7 exhibits a negative divergence between the LFI and LMI, leading the latter to decline from 21 November. Both indicators trigger simultaneously buy and sell signals. The whipsaws of the LFI can be filtered by the LMI and vice versa.

Pressure Index and Integral Pressure Index

By definition, pressure is the ratio of force to the area over which that force is distributed. If the same force amount is applied on different areas, where A_1 is greater than A_2 then, the pressure on A_1 is less than A_2.

Figure 8. Pressure Concept

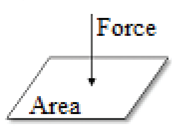
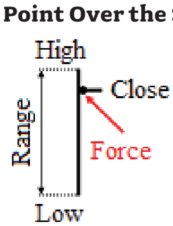


Figure 9. Buying/Selling Force Moving the Closing Price Point Over the Session's Range



The pressure index *PRI* measures the buying and selling pressure over a certain range within a time interval by moving around its zero line. The index indicates a rise in buying pressure when it crosses above the zero line and a rise in selling pressure when it crosses below the zero line level.

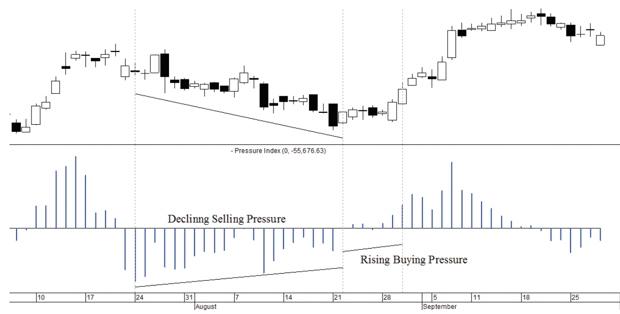
The buying and selling force moves the last price during the session to form a range with low and high boundaries. The range represents the sum of every point over which the price is executed. Since the price moves in one dimension only—*upward or downward*—we will be concerned with one component of the area, which is the height, or the range that prices are moving in. The formula describing the pressure index for today's session is therefore

$$PRI_{today} = \frac{Force}{Range} = \frac{V}{H\text{-}L} . EMA_{14}\left(C\text{-}2C_y\text{+}C_{by}\right)$$

The pressure index is expressed by

$$PRI = EMA_{14} \text{ of } PRI_{Today}$$

Figure 10. NASDAQ — Daily Values of Ebay Inc. (EBAY.O)

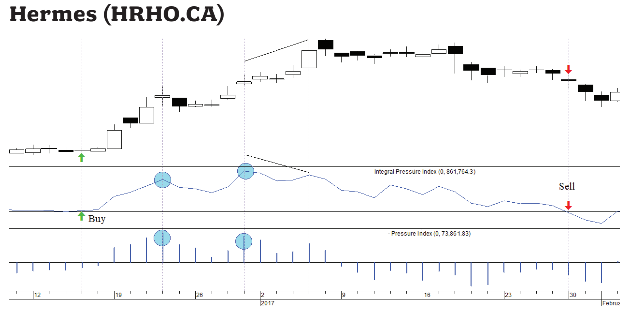


The integral pressure index *IPRI* is a leading indicator. It minimizes the sensitivity of the pressure index. The formulas of the IPRI are described by

$$IPRI = \frac{1}{Range} \int Force \, dt = \frac{Momentum}{Range}$$

$$IPRI_{today} = \frac{V.(C\text{-}C_y)}{H\text{-}L} ; \ IPRI = EMA_{14} \text{ of } IPRI_{today}$$

Figure 11. Egyptian Stock Exchange — Daily Values of EFG Hermes (HRHO.CA)



In Figure 11, the pressure index has made a negative divergence with the IPRI, leading the latter to decline at the beginning of 2017. During the first week of January, the IPRI has traced a lower high while prices were still rising. The weakness in the buying pressure led the prices to move sideways until a sell signal was generated at 30 January.

Figure 12. Egyptian Stock Exchange — Weekly Values of Nile Cotton Gin (NCGC.CA)

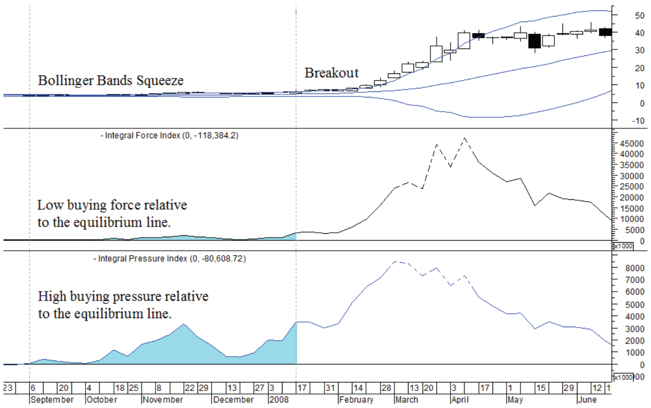
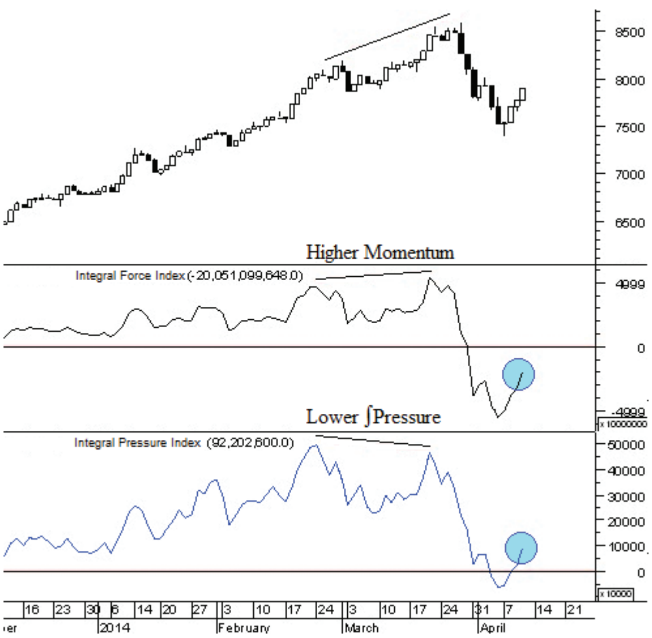


Figure 12 demonstrates a modest buying force and momentum until the beginning of 2008. This was reflected by a squeeze in the Bollinger bands. On the contrary, the buying pressure within the same period was rising sharply preceding the price breakout. The dotted peaks of the indicators show a negative divergence, which led the stock's momentum to decline after 17 April.

Figure 13. Egyptian Stock Exchange — Daily Values of EGX30 index (.EGX30)



The pressure is leading to force as the value of the latter is changed by the value of area or range. Figure 13 shows a negative divergence between the IPRI, IFI, and prices. During the month of March, prices were increasing with higher buying momentum but lower buying pressure. When prices declined during April, the bears were controlling by high selling force, but their selling pressure was modest; therefore, the bulls re-pressured quickly, and the IPI generated a buy signal before the IFI or LMI.

Strength Index and Integral Strength Index

In scientific context, strength is the ability to withstand an applied stress. It is different than force, pressure, and power.

Figure 14. Equal Stress on Different Types of Bars With the Same Length

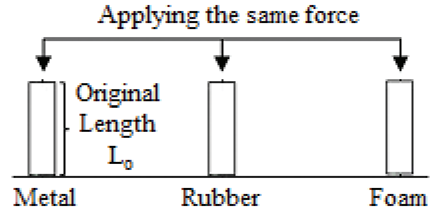
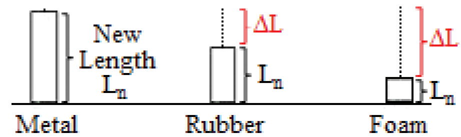


Figure 15. Strength Comparison of Different Types of Bars



To elaborate, Figures 14 and 15 show a hypothetical example about three bars made of metal, rubber, and foam. Being exposed to the same amount of *stress,* the bars' lengths are expected to shrink by different values. The bar made of foam shrunk the most, as it has the lowest strength. The result of stress is *strain,* which is a measure of the degree of deformation, reduction, or growth. In other words, strain is the ratio of the change in length ΔL to the original length L_0 of the body under stress.

$$\text{Strain} = \frac{L_{original} - L_{new}}{L_{original}} = \frac{\Delta L}{L_o}$$

Strength is the ratio of stress to strain.

$$\text{Strength} = \frac{\text{Stress}}{\text{Strain}} = \frac{\text{Force/Area}}{\Delta L / L_o}$$

Figure 16. The Structure of Japanese Candlesticks

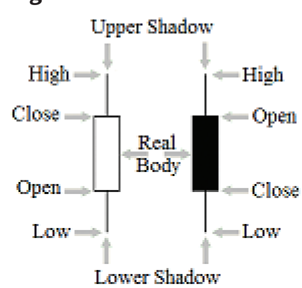
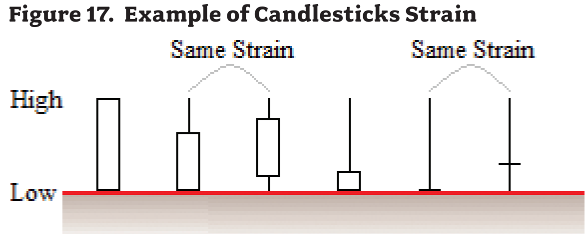


Figure 17. Example of Candlesticks Strain



Let us imagine that prices move in an ideal uptrend, where the selling momentum and pressure are almost insignificant. Prices tend to close at their highs to form bullish candlesticks without shadows. The first long white candle in Figure 17 highlights this case, where sellers could not succeed to exert their pressure on buyers. The original length L_0 is the range $H–L$ of the session, and the new length L_n is the magnitude of the real body. Hence, ΔL is the magnitude of the shadows that refer to how far the sellers were able to interfere. The smaller the strain, shadows, the higher the buying/selling strength.

The strength index *SI* is a leading indicator to the pressure index. It measures the ability of buyers to resist sellers and vice versa. SI of today is the ratio of the latest pressure index value to the strain of today.

$$SI_{today}=\frac{V.EMA_{14}(C\text{-}2C_y+C_{by})/(H\text{-}L)}{[(H-L)\text{-}|C-O|]/(H\text{-}L)}$$

Hence,

$$SI_{today}=\frac{V.EMA_{14}(C\text{-}2C_y+C_{by})}{(H\text{-}L)\text{-}|C\text{-}O|}$$

The drawback of the previous formula lies in the denominator part. The latter may yield a zero value if the range is equal to the magnitude of the real body. To overcome this inconsistency, we increase the range by a small percentage—strain factor *SF*. Therefore,

$$SI_{today}=\frac{V.EMA_{14}(C\text{-}2C_y+C_{by})}{SF.(H\text{-}L)\text{-}|C\text{-}O|}$$

The default value of the strain factor is 1% or 1.01. Finally, the formula of the strength index is described by

$$SI= EMA_{14} \text{of } SI_{today}$$

The integral strength index *ISI* is a leading indicator to the integral pressure index and prices. It is mostly useful in defining the turning points, where bulls are resisting bears and vice versa.

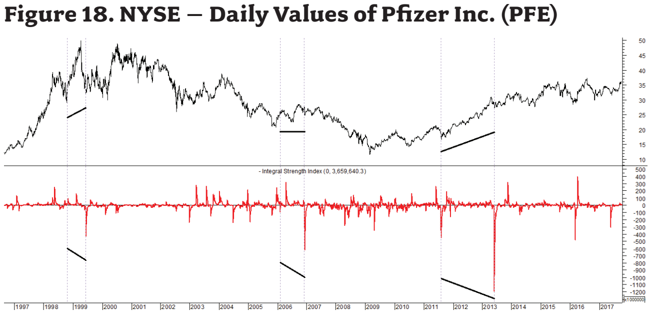
$$ISI=\frac{\text{Momentum/Range}}{\text{Strain}}$$

The formula of the ISI is described as

$$ISI_{today}=\frac{V.(C\text{-}C_y)}{1.01(H\text{-}L)\text{-}|C\text{-}O|}$$

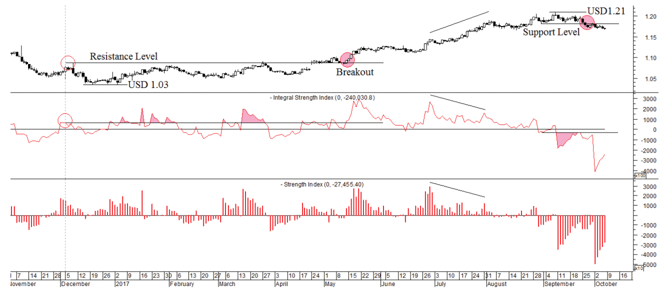
$$ISI= EMA_{14} \text{of } ISI_{today}$$

Figure 18. NYSE — Daily Values of Pfizer Inc. (PFE)



Until the end of 1990s, the stock shown in Figure 18 was moving in an uptrend. Although prices have traced a higher low, the strength of the bears increased by the mid of 1999 to hinder the bulls from targeting a higher high above USD 50.04. At 2007, the selling strength increased once again to let the stock continue its downtrend. In 2013, prices turned back to move in a weaker uptrend than the one ended in 1999 due to the extreme rising strength of bears in 2013. Afterwards, prices moved sideways, as the sellers resistance to buyers was relatively too high.

Figure 19. Daily Values of Euro vs. Dollar Currency (EUR=)



As demonstrated in Figure 19, the ISI crossed its equivalent level of resistance several times earlier than the price breakout. Such strength forced the prices to be curbed higher than USD 1.03. During the month of July, prices were rising, while the ISI and SI indicated a lower buying strength, which permitted the sellers to balance the supply with demand for the following quarter. In September and October, the rising strength of sellers does not mean that the supply exceeded demand to lower prices. However, they hinder the buyers to push prices above the peak at USD 1.21.

Figure 20. Egyptian Stock Exchange — Weekly Values of Sidi Kerir Petrochemicals (SKPC.CA)

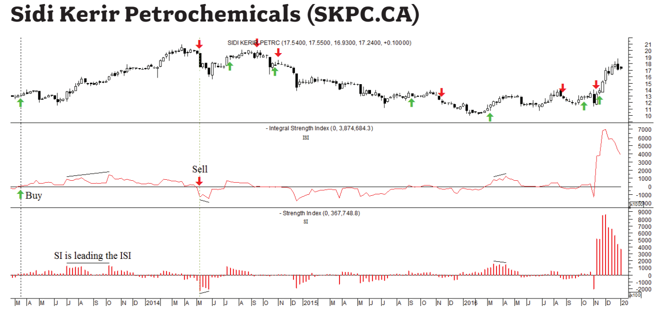


Figure 20 shows the combined signals of the SI and ISI. Both indicators must cross above their zero levels to generate buy signals and vice versa. The crossovers do not have to be at the same session. However, their simultaneous crossovers are very significant, as they refer to a synchronization of their cycles.

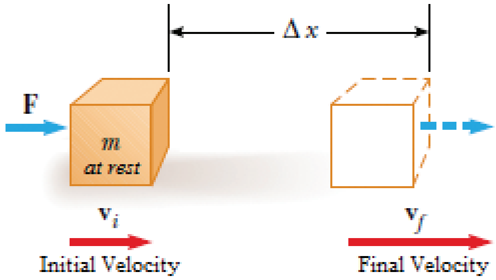
Power Index and Integral Power Index

Power is defined as the time rate of energy transfer or work done *W*. To calculate the needed work to move an object, we simply find the product of the distance Δx that the object has traveled and the applied force *F* pushing that object. Therefore, W=F.Δx, while the average power *P* is the work done over time Δt. In this paper, the terms *average power* and *power* have the same meaning.

$$\text{Power}=\frac{\text{Work Done}}{\text{Time Interval}}=F.\frac{\Delta x}{\Delta t}$$

Apparently, P=F.*v* where we use the fact that the velocity *v*= Δx /Δt. The power by which anything moves is not the same as pressure or force but proportional to the latter.

Figure 21. An Object Undergoing a Displacement Δx With Velocity Under an Applied Force F *(adapted and edited from* Physics for Scientists and Engineers, *2004, p. 193)*



By applying this solid concept on prices, this paper proposes the power index *PWRI.* It measures the buying and selling power within a time interval by moving around its zero line. One-day price power can be written as

$$PWRI_{today}=V.(C-C_y).EMA_{14}(C-2C_y+C_{by})$$

The PWRI today's value may turn positive if the price velocity and acceleration are both negative. To overcome this problem, we may add a condition to the above equation:

- If $C>C_y$, $PWRI_{today}$ is positive.
- If $C\leq C_y$, $PWRI_{today}$ is negative.

The power index is expressed by

$$PWRI=EMA_{14} \text{ of } \pm PWRI_{today}$$

To calculate the integral power index *IPWRI* we just integrate the force part turning back to momentum. Hence, the integral power is the product of momentum and velocity.

$$IPWRI_{today}=V.(C-C_y)^2$$

- If $C>C_y$, $IPWRI_{today}$ is positive.
- If $C\leq C_y$, $IPWRI_{today}$ is negative.

Continuously, the squared part will yield positive values. By adding the previous conditions,

$$IPWRI=EMA_{14} \text{of} \pm IPWRI_{today}$$

Figure 22. Egyptian Stock Exchange — Daily Values of Global Telecom (GTHE.CA)

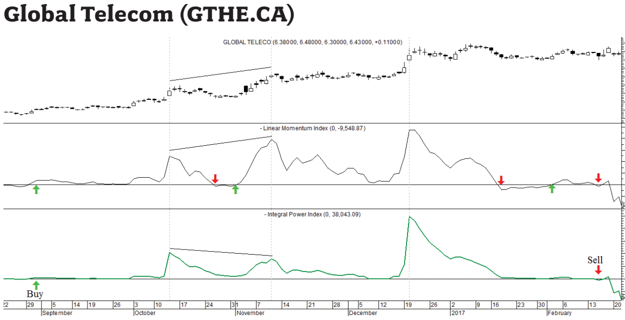


Figure 22 shows the difference between the integral force or linear momentum and the integral power. Prices were moving in an uptrend during the last quarter of 2016. Although the price momentum was rising during the month of November, the buying power was declining to slow down the increase in prices. As demonstrated, the IPWRI has generated one trade only unlike the LMI. The power indicators are leading indicators and much more sensitive to the high velocities of prices because the change in price is squared unlike the force and momentum indicators.

Figure 23. NYSE — Daily Values of Apple Inc.(AAPL.O)

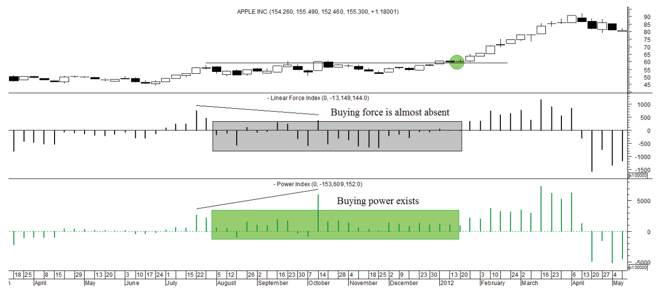


Figure 23 shows the difference between the power and linear force index. The PWRI has increased pointing to a high buying power while prices were still moving sideways.

Intensity Index and Integral Intensity Index

Intensity is the power per unit area. We can think of intensity as how fast the pressure is exerted.

Figure 24. Gas Molecules Exerting Pressure on the Walls of Two Containers

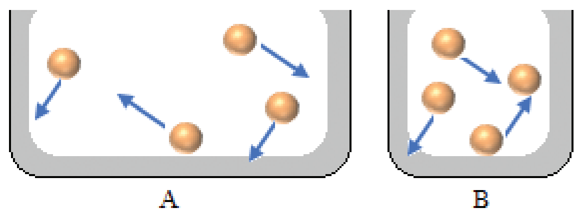
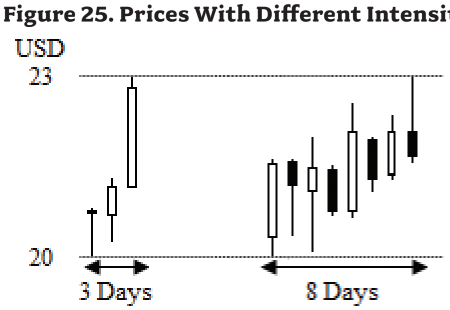


Figure 24 demonstrates the movement of gas molecules in small and large containers. The pressure exerted on the walls of container B is quicker than the pressure exerted on the walls of the larger container A. In other words, the intensity of the moving molecules in container B is higher than A.

Figure 25. Prices With Different Intensities



The price has displaced from USD 20 to 23 in three days. Another time, it took eight days for prices to reach USD 23. In the first case, we say that the price movement was highly intense.

$$\text{Price Intensity} = \frac{\text{Power}}{\text{Range}} = \frac{\text{Force.Velocity}}{\text{Range}}$$

Since pressure is equal to *Force/Range,* then we can rewrite the price intensity as the product of price pressure and velocity. We can think of price intensity as how steep prices move.

$$\text{Price Intensity} = \text{Pressure.Velocity}$$

The intensity index *II* measures the buying and selling intensity within a time interval by moving around its zero line. One-day price intensity is expressed by

$$II_{today}=\frac{V.(C\text{-}C_y).EMA_{14}(C\text{-}2C_y\text{+}C_{by})}{H\text{-}L}$$

- If $C>C_y$, II_{today} is positive.
- If $C\leq C_y$, II_{today} is negative.

$$II= EMA_{14} of \pm II_{today}$$

$$III_{today}=\frac{V.(C\text{-}C_y)^2}{H\text{-}L}$$

- If $C>C_y$, III_{today} is positive.
- If $C\leq C_y$, III_{today} is negative.

Integral Intensity Index (III)=$EMA_{14}$of$\pm III_{today}$

Figure 26. Egyptian Stock Exchange — Weekly Values of Commercial International Bank (COMI.CA)

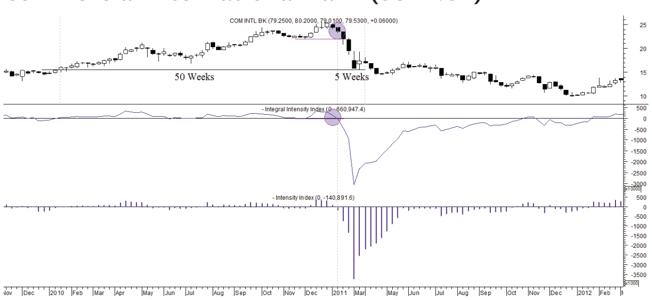
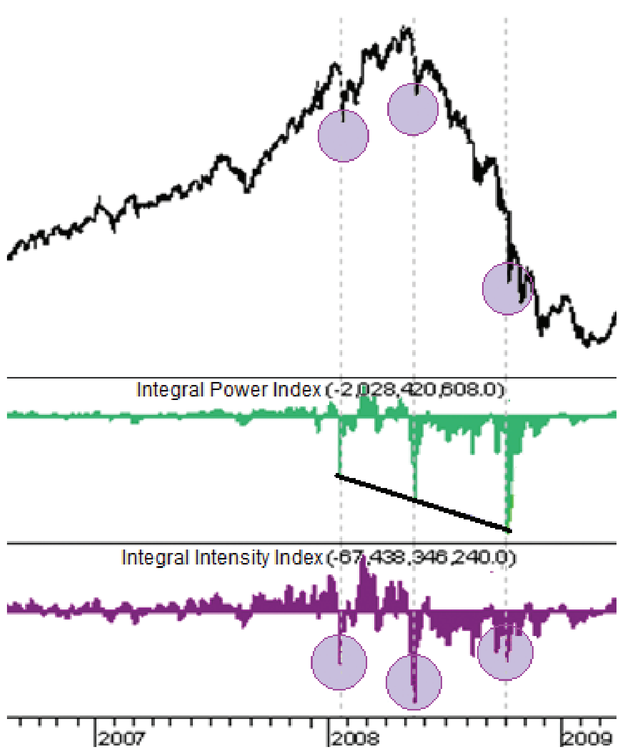


Figure 26 shows the leading intensity indicators pointing to an increase for the selling intensity and the sharp decline of prices.

Figure 27. Egyptian Stock Exchange — Weekly Values of EGX30 index (.EGX30)



During the trend reversal of EGX30, as shown in Figure 27, prices increased with the higher low while the selling power and intensity increased, paving the way to a powerful and sharp decline afterwards. During the downtrend in 2008, the selling power increased further, but this time the selling intensity has diminished leading the power of bears to be reduced. As an effect, prices continued the downtrend with less intensity, power, and momentum.

Dynamic Strength Index and Integral Dynamic Strength Index

The sole purpose of the dynamic strength index *DSI* and the integral dynamic strength index *IDSI* is to lead their intensity indicator peers. The dynamic strength is the product of strength and velocity; hence, the formulas describing the DSI and IDSI are

$$DSI_{today}=\frac{V(C\text{-}C_y).EMA_{14}(C\text{-}2C_y\text{+}C_{by})}{SF.(H\text{-}L)\text{-}|C\text{-}O|}$$

$$IDSI_{today}=\frac{V.(C\text{-}C_y)^2}{SF.(H\text{-}L)\text{-}|C\text{-}O|}$$

Where the default value of SF is 1% or 1.01.

- If $C>C_y$, $DSI_{today}/IDSI_{today}$ are positive.
- If $C\leq C_y$, $DSI_{today}/IDSI_{today}$ are negative.

$$DSI= EMA_{14} of \pm DSI_{today}$$

$$IDSI= EMA_{14} of \pm IDSI_{today}$$

Figure 28. NYSE — Weekly Values of Exxon Mobil (XOM)

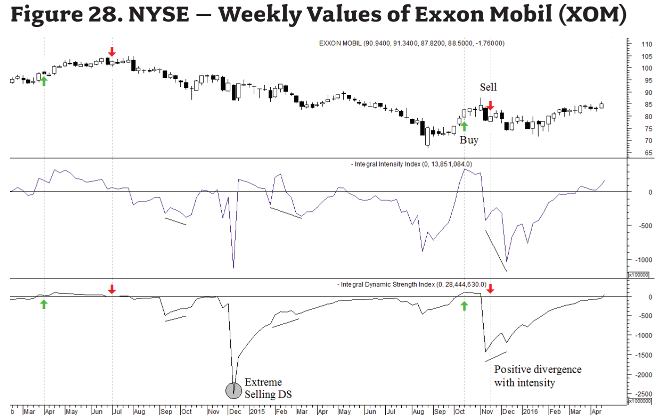


Figure 28 shows the signals generated by the IDSI. The extreme selling dynamic strength hinders the bulls to take control and paves the way for the bears to pressurize again and curb the market. The IDSI also leads the price intensity as demonstrated.

Testing Results

Testing has been carried out on the Saudi and Egyptian markets for the last 10 years on the daily timeframe. The buy and hold strategy benchmarked the results by -9.11% and 79.74% for the Saudi and Egyptian indices, respectively—TASI and EGX30.

The buy signals are tested during uptrends. To define the uptrend in the system, stocks closing above their 14-day EMA are considered while the ADX is above 14. During uptrends, the bulls control the market, and the indicators move above their centerlines with an increase in their momentum.

The denominators of the pressure and intensity indicators consist of the range $H{-}L$ of the days. Some data are erroneously having zero range. To overcome this problem, the high fields for the whole data set are increased by 1 percent.

Table 3a. Saudi Stock Exchange — Testing Results of Performance Indicators 1/1/2007–1/1/2017

	Linear Force Index	Pressure Index	Strength Index
Net % Profit	239.66	292.34	168.03
Exposure %	76.17	69.57	78.17
Annual Return %	13.01	14.66	10.37
Max. Sys. % Draw-down	-37.4	-33.29	-39.38
Trades	4290	6192	4406
Avg. Profit/Loss	55.86	47.21	38.14
Avg. % Profit/Loss	0.75	0.57	0.64
Avg. Bars Held	10.52	7.22	10.37
Winners	1472	2040	1449
% of Winners	34.31	32.95	32.89
Avg. Profit	718.62	620.7	600.72
Avg. % Profit	8.24	6.56	8.12
Losers	2818	4152	2957
% of Losers	65.69	67.05	67.11
Avg. Loss	-290.33	-234.56	-237.54
Avg. % Loss	-3.16	-2.38	-3.02
Ratios			
Risk-Reward	0.77	0.82	0.67
Profit Factor	1.29	1.3	1.24
Payoff	2.48	2.65	2.53

Table 3b. Saudi Stock Exchange — Testing Results of Performance Indicators 1/1/2007–1/1/2017

	Power Index	Intensity Index	Dynamic Strength Index
Net % Profit	89.21	84.3	71.32
Exposure %	84.19	82.91	84.41
Annual Return %	6.59	6.31	5.53
Max. Sys. % Draw-down	-53.96	-55.66	-53.79
Trades	2396	2959	2407
Avg. Profit/Loss	37.23	28.49	29.63
Avg. % Profit/Loss	0.85	0.66	0.79
Avg. Bars Held	18.89	15.35	18.72
Winners	810	969	813
% of Winners	33.81	32.75	33.78
Avg. Profit	857.2	666.27	720.29
Avg. % Profit	12.48	10.83	12.12
Losers	1586	1990	1594
% of Losers	66.19	67.25	66.22
Avg. Loss	-381.54	-282.07	-322.63
Avg. % Loss	-5.1	-4.29	-4.99
Ratios			
Risk-Reward	0.4	0.47	0.38
Profit Factor	1.15	1.15	1.14
Payoff	2.25	2.36	2.23

Table 4a. Saudi Stock Exchange — Testing Results of Integral Performance Indicators 1/1/2007–1/1/2017

	Integral Force Index	Integral Pressure Index	Integral Strength Index
Net % Profit	45.54	191.26	151.82
Exposure%	84.14	81.56	83.41
Annual Return%	3.83	11.29	9.68
Max. Sys% Drawdown	-56.77	-54.34	-50.06
Trades	2922	3765	3145
Avg. Profit/Loss	15.58	50.8	48.27
Avg. % Profit/Loss	0.5	0.87	0.88
Avg. Bars Held	15.21	12.44	14.62
Winners	813	1036	899
% of Winners	27.82	27.52	28.59
Avg. Profit	612	844.8	881.41
Avg. % Profit	11.99	11.11	12.01
Losers	2109	2729	2246
% of Losers	72.18	72.48	71.41
Avg. Loss	-214.33	-250.62	-285.2
Avg. % Loss	-3.93	-3.02	-3.58
Ratios			
Risk-Reward	0.35	0.61	0.55
Profit Factor	1.1	1.28	1.24
Payoff	2.86	3.37	3.09

Table 4b. Saudi Stock Exchange — Testing Results of Integral Performance Indicators 1/1/2007–1/1/2017

	Integral Power Index	Integral Intensity Index	Integral Dynamic Strength Index
Net % Profit	-7.44	42.44	55.13
Exposure %	86.15	85.23	85.16
Annual Return %	-0.77	3.6	4.49
Max. Sys. % Draw-down	-58.31	-57.33	-55.36
Trades	2075	2455	2149
Avg. Profit/Loss	-3.58	17.29	25.66
Avg. % Profit/Loss	0.22	0.59	0.73
Avg. Bars Held	21.15	18.03	20.67

Winners	643	738	694
% of Winners	30.99	30.06	32.29
Avg. Profit	543.5	629.02	726.09
Avg. % Profit	13	12.32	12.96
Losers	1432	1717	1455
% of Losers	69.01	69.94	67.71
Avg. Loss	-249.23	-245.65	-308.44
Avg. % Loss	-5.52	-4.45	-5.1
Ratios			
Risk-Reward	0.07	0.35	0.31
Profit Factor	0.98	1.1	1.12
Payoff	2.18	2.56	2.35

Table 5a. Egyptian Stock Exchange — Testing Results of Performance Indicators 1/1/2007–1/1/2017

	Linear Force Index	**Pressure Index**	**Strength Index**
Net % Profit	1167.24	987.61	844.31
Exposure %	29.18	28.76	34.35
Annual Return %	30.11	28.07	26.21
Max. Sys. % Draw-down	-16.33	-13.44	-18.55
Trades	8225	10272	8809
Avg. Profit/Loss	141.91	96.15	95.85
Avg. % Profit/Loss	2.04	1.56	1.47
Avg. Bars Held	12.45	9.16	11.35
Winners	2839	3565	2965
% of Winners	34.52	34.71	33.66
Avg. Profit	787.44	556.43	608.03
Avg. % Profit	13.77	11.05	12.4
Losers	5386	6707	5844
% of Losers	65.48	65.29	66.34
Avg. Loss	-198.35	-148.51	-164.01
Avg. % Loss	-4.14	-3.49	-4.07
Ratios			
Risk-Reward	0.68	0.84	0.8
Profit Factor	2.09	1.99	1.88
Payoff	3.97	3.75	3.71

Table 5b. Egyptian Stock Exchange — Testing Results of Performance Indicators 1/1/2007–1/1/2017

	Power Index	**Intensity Index**	**Dynamic Strength Index**
Net % Profit	666.66	596.85	714.83
Exposure %	54.24	47.83	49.1
Annual Return %	23.51	22.29	24.29
Max. Sys % Drawdown	-31.22	-27.67	-30.87
Trades	6307	6991	6714
Avg. Profit/Loss	105.7	85.37	106.47
Avg. % Profit/Loss	2.53	2.15	2.51
Avg. Bars Held	21.38	17.64	19.79
Winners	2126	2333	2262
% of Winners	33.71	33.37	33.69
Avg. Profit	725.03	570.58	720.91
Avg. % Profit	18.66	16.29	18.35
Losers	4181	4658	4452
% of Losers	66.29	66.63	66.31
Avg. Loss	-209.22	-157.65	-205.72
Avg. % Loss	-5.68	-4.94	-5.54
Ratios			
Risk-Reward	0.82	0.86	0.72
Profit Factor	1.76	1.81	1.78
Payoff	3.47	3.62	3.5

Table 6a. Egyptian Stock Exchange — Testing Results of Integral Performance Indicators 1/1/2007–1/1/2017

	Integral Force Index	**Integral Pressure Index**	**Integral Strength Index**
Net % Profit	680.08	733.06	655.53
Exposure %	54.22	44.71	51.69
Annual Return %	23.73	24.58	23.32
Max. Sys. % Draw-down	-36.18	-23.84	-32.51
Trades	7232	8470	8074
Avg. Profit/Loss	94.04	86.55	81.19
Avg. % Profit/Loss	2.26	1.95	1.99
Avg. Bars Held	18.5	15.1	16.5
Winners	2145	2468	2426
% of Winners	29.66	29.14	30.05
Avg. Profit	699.06	622.02	614.38
Avg. % Profit	18.68	16.51	17.07
Losers	5087	6002	5648
% of Losers	70.34	70.86	69.95
Avg. Loss	-161.08	-133.64	-147.83
Avg. % Loss	-4.67	-4.03	-4.49
Ratios			
Risk-Reward	0.9	0.89	0.98
Profit Factor	1.83	1.91	1.79
Payoff	4.34	4.65	4.16

Table 6b. Egyptian Stock Exchange — Testing Results of Integral Performance Indicators 1/1/2007–1/1/2017

	Integral Power Index	Integral Intensity Index	Integral Dynamic Strength Index
Net % Profit	530.33	639.22	767.12
Exposure %	62.04	55.63	53.43
Annual Return %	21.03	23.04	25.1
Max. Sys. % Drawdown	-32.28	-35.34	-39.72
Trades	5662	6674	6360
Avg. Profit/Loss	93.66	95.78	120.62
Avg. % Profit/Loss	2.51	2.45	2.85
Avg. Bars Held	24.04	20.67	22.49
Winners	1733	2061	2008
% of Winners	30.61	30.88	31.57
Avg. Profit	743.75	688.17	858.42
Avg. % Profit	21.33	19.36	21.24
Losers	3929	4613	4352
% of Losers	69.39	69.12	68.43
Avg. Loss	-193.07	-168.89	-219.8
Avg. % Loss	-5.79	-5.1	-5.64
Ratios			
Risk-Reward	0.79	0.9	0.77
Profit Factor	1.7	1.82	1.8
Payoff	3.85	4.07	3.91

Discussion

From the previous section, we notice that the integral performance indicators have a fewer number of trades than the performance indicators. This result is normal, as the integral indicators are less sensitive than their peers. Moreover, the power, intensity, and dynamic strength are less sensitive than the force, pressure, and strength indicators. The same applies for their integrals. Therefore, the integrals of power, intensity, and dynamic strength indicators are more inclined to be medium-term indicators.

Table 7. The Relation Among Performance Indicators and Their Integrals

	Price		Price
Price Velocity Multiplied by	Force	Yields	Power
	Pressure		Intensity
	Strength		Dynamic Strength
	Momentum		Integral Power
	Integral Pressure		Integral Intensity
	Integral Strength		Integral Dynamic Strength

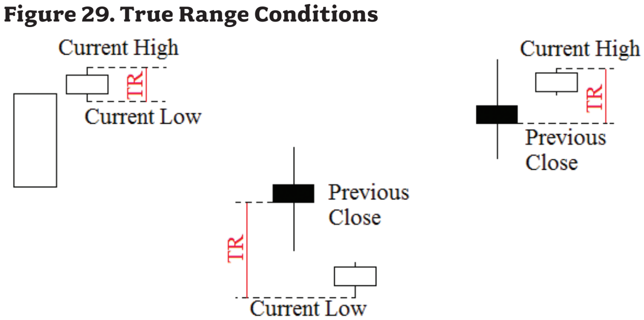
The power index and the nominators of the intensity and dynamic strength index may have an absolute value. However, the shape and the value of the indicators will be slightly different. Although the results of the performance indicators mostly exceeded the results of their integral peers during testing, the latter may outperform in other markets and in different timeframes.

True Range

Developed by J. Welles Wilder, the true range *TR* is a set of conditions that helps in measuring volatility. Stocks and commodities are frequently subject to gaps that occur when the instrument opens below or above the previous session's range. Indicators based on the high–low range would fail to capture volatility from gaps. Wilder created the true range to capture this missing volatility. TR is defined as the highest absolute value of the following:

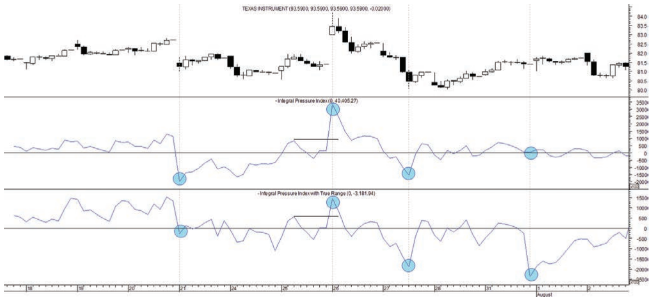
- Current High less the Current Low.
- Current High less the Previous Close.
- Current Low less the Previous Close.

Figure 29. True Range Conditions



The *H-L* part in the pressure, intensity, strength, and dynamic strength indicators can be substituted by the TR conditions based on the traders need. As shown in Figure 30, the effect of the true range on the integral pressure index during gaps lowers the IPRI average, as the momentum part will be divided by a higher range *TR*.

Figure 30. NYSE — Hourly Values of Texas Instruments (TXN.O)



The Lead Map

Since price acceleration is leading to price velocity, the performance indicators are leading by turn to their integral peers.

Figure 31a. Chart of Leading Indicators

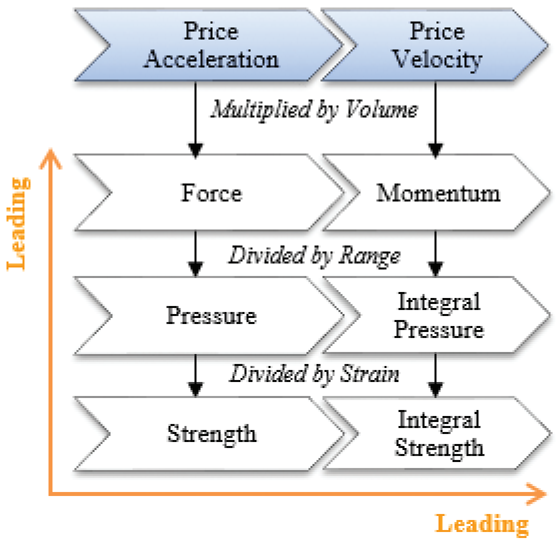
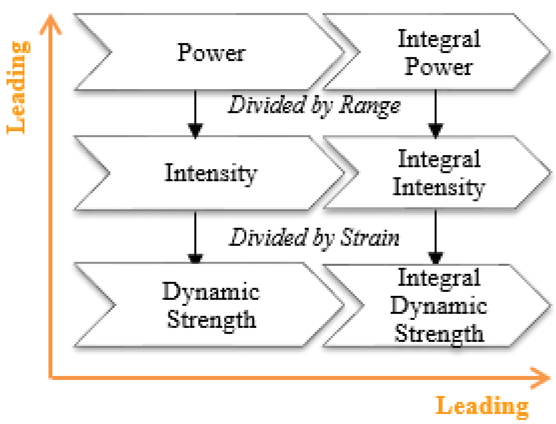


Figure 31b. Chart of Leading Indicators

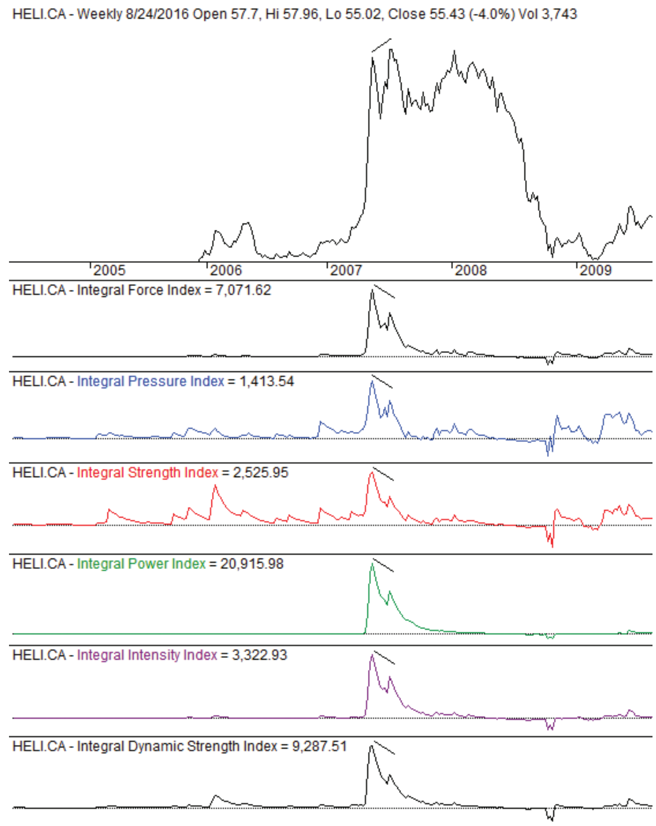


Another type of lead is resulted from the division process of the indicators. For example, the price pressure is a result to the change of price force by range. Hence, the pressure indicators are leading to force indicators. All the integral performance indicators are also leading to prices.

Divergence

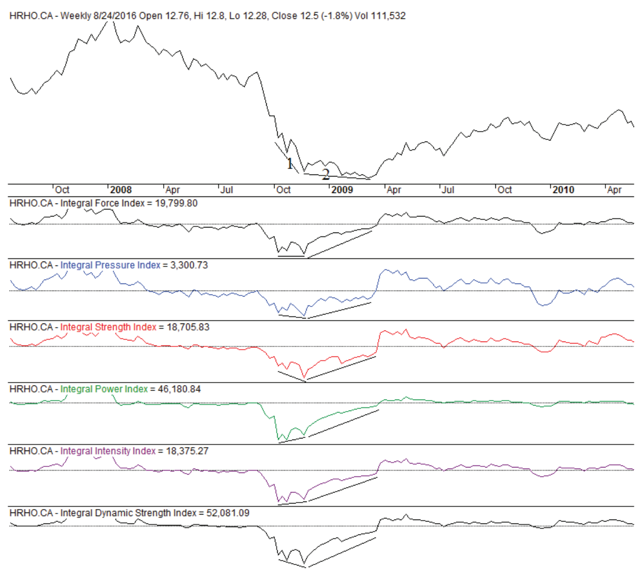
We have demonstrated in previous examples how indicators diverge with prices and how they lead each other. In this section, we highlight the importance of simultaneous divergence.

Figure 32. Egyptian Stock Exchange — Weekly Values of Heliopolis Housing (HELI.CA)



In Figure 32, all the integral performance indicators have traced a negative divergence with prices. All the elements of market performance have agreed on the bull's weakness at the peak. In Figure 33, the stock was moving in a downtrend. At the first labeled decline, only the power and intensity indicators have traced a positive divergence with prices. Yet, the stock continued its decline at lower momentum. At the second decline, all the indicators have traced a positive divergence to agree on the weakness of bears. Obviously, the second divergence is the most significant one.

Figure 33. Egyptian Stock Exchange — Weekly Values of EFG Hermes (HRHO.CA)



Combined and Synchronized Signals

Combined signals is an additional trading tactic, which includes all the successive buy/sell signals of the performance indicators *PIs* and the integral performance indicators *IPIs.*

Synchronized signals is the second tactic, which includes the simultaneous buy/sell signals for the whole set of indicators.

Two templates are created to analyze the market strength and weakness. The first template embraces the signals of the PIs, while the second template embraces the signals generated by the IPIs. From the lead map, we can deduce that the PIs template is leading the IPIs one. The structure of both templates involves the following,

- Strength candles: the values of all the template's indicators are greater than zero.
- Weak candles: the values of all the template's indicators are less than zero.
- Neutral candles: the values of a part of the template's indicators are greater than zero, while the remaining indicators have values less than zero.

Figure 34. NYSE — Weekly Values of Boeing Co (BA)

In Figure 34, the combined buy/sell signals are generated when candles embrace strength/weakness. Neutral candles require no action. The IPI template will not generate its signals before the PI template. From an analytical perspective, Table 8 shows the strength/weakness relation between both templates and their effect on prices.

Table 8. Strength and Weakness Analysis

Area	PI Template	IPI Template	Relative Effect on Prices
1	Neutral	Strength	Weakness
2	Weakness	Strength	Weakness
3	Weakness	Neutral	Weakness
4	Neutral	Strength	Weakness
5	Neutral	Weakness	Strength
6	Neutral	Weakness	Strength

To elaborate, prices were moving in an uptrend until July 2007, before the double top reversal pattern was formed. Although the IPI template shows strength for the candles in areas 1/2/3/4, the PI template shows neutral and weak candles for the same areas. Such a comparison indicates an overall weakness in prices. Afterwards, both templates agreed on weakness before prices break the neckline of the formation. Subsequently, prices were moving in a downtrend until areas 5/6, where the neutral candles along with the weak candles of the IPI template refer to a marginal strength. Consequently, prices declined with lower momentum and started to move sideways.

On another note, the synchronized signals are usually significant, as the leading and main cycles of PI and IPI, respectively, have agreed on simultaneous crossovers to the centerlines of the indicators.

Conclusion

The linear momentum concept prepares the ground for recategorizing several indicators in technical analysis. Along with the performance indicators, they dissect the market strength into elements that help in analyzing the price action thoroughly.

Table 9. Recategorizing Selected Indicators

Velocity	Acceleration	Momentum
Wilder's Momentum	AC Oscillator	Elder's Force
MACD	MACD Histogram	Linear Momentum
RSI		Money Flow Index
Parabolic SAR		
TRIX		

This paper has separated bullish and bearish momentum to construct leading indicators. The lead among strength, pressure, and momentum occurs without increasing the indicator's sensitivity drastically. The same applies for the dynamic strength, intensity, and power indicators. In addition, the performance indicators and their integrals embrace the price volatility beside its momentum.

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Software and Data

Testing was performed by AmiBroker software.

Data and charts used in this article are provided by Thomson Reuters data feed and Metastock software.

Appendix

Indicators Codes for Amibroker

```
n=14;
SF= 1.01;
Range= H-L;
RealBody=abs(C-O);
Cy= Ref(C,-1);
Velocity= C-Cy;
VelocityYesterday= Ref(Velocity,-1);
AccelerationToday= Velocity-VelocityYesterday;
Acceleration= EMA(AccelerationToday,n);
Force= Volume*Acceleration;
Momentum= Volume*Velocity;
```

Linear Force Index

```
LinearForceToday= Volume*Acceleration;
LinearForce= EMA(LinearForceToday,n);
```

Pressure Index

```
PressureToday= Force/Range;
Pressure= EMA(PressureToday,n);
```

Strength Index

```
StrengthToday= Force/(SF*Range-RealBody);
Strength= EMA(StrengthToday,n);
```

Power Index

```
PowerEquation= Force*Velocity;
PowerToday= iif(C>Cy,PowerEquation,-PowerEquation);
Power= EMA(PowerToday,n);
```

Intensity Index

```
IntensityEquation= Force*Velocity/Range;
IntensityToday= iif(C>Cy,IntensityEquation,-IntensityEquation);
Intensity= EMA(IntensityToday,n);
```

Dynamic Strength Index

```
DynamicStrengthEquation= Force*Velocity/(SF*Range-RealBody);
DynamicStrengthToday= iif(C>Cy,DynamicStrengthEquation,-
    DynamicStrengthEquation);
DynamicStrength= EMA(DynamicStrengthToday,n);
```

Integral Force Index

(Linear Momentum Index)

```
IntegralForceToday= Momentum;
IntegralForce= EMA(IntegralForceToday,n);
```

Integral Pressure Index

```
IntegralPressureToday= Momentum/Range;
IntegralPressure= EMA(IntegralPressureToday,n);
```

Integral Strength Index

```
IntegralStrengthToday= Momentum/(SF*Range-RealBody);
IntegralStrength= EMA(IntegralStrengthToday,n);
```

Integral Power Index

```
IntegralPowerEquation= Momentum*Velocity;
IntegralPowerToday= iif(C>Cy,IntegralPowerEquation,-
    IntegralPowerEquation);
IntegralPower= EMA(IntegralPowerToday,n);
```

Integral Intensity Index

```
IntegralIntensityEquation= Momentum*Velocity/Range;
IntegralIntensityToday= iif(C>Cy,IntegralIntensityEquation,-
    IntegralIntensityEquation);
IntegralIntensity= EMA(IntegralIntensityToday,n);
```

Integral Dynamic Strength Index

```
IntegralDynamicStrengthEquation= Momentum*Velocity/
    (SF*Range-RealBody);
IntegralDynamicStrengthToday= iif(C>Cy,IntegralDynamicStrengt
    hEquation,-IntegralDynamicStrengthEquation);
IntegralDynamicStrength= EMA(IntegralDynamicStrengthToday,n);
```

Trend Analysis Using B-Xtrender

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Abstract

From the beginning of times of technical analysis, there has been the ultimate pursuit of a trend-following technical analyst to identify and enter an ongoing trend, thus also underlining the ultimate problem (i.e., determining when to exit the trade by either booking profits or reversing his open positions).

Overbought and oversold levels have become commonly sought out by technical analysts. Many trend-following tools help him in this pursuit, with an arsenal of technical indicators.

Most of the existing indicators fail to indicate scaling (up or down) signals for an in-progress trend. They also fall short in differentiating a trend change from a partial retracement. This myopic vision of the trend often leads to ignoring the major trend and falling into the minor trap.

To solve the above mentioned problem, I present the B-Xtrender, which helps determine the intermediate and major trend, along with providing precise entries, exits and scaling signals. It also helps differentiate a short-term correction from a trend change and can be used to analyze markets across all spectra.

After rigorously testing for over six years, across different markets and different time frames, the B-Xtrender was found to be highly efficient.

Introduction

Big money is made in the stock market by being on the right side of the major moves. The idea is to get in harmony with the market. It's suicidal to fight trends. They have a higher probability of continuing than not.

—Martin Zweig

The B-Xtrender elucidates the dilemma of differentiating a trend change from a minor correction, thus providing specific entry, scaling and exit signals. It is an indicator created to give a single glance of the ongoing trend. Even a casual look at the system can acquaint the viewer about the long-term and short-term trend.

Material and Methods

The Design

Two indicators used in conjunction constitute the B-Xtrender. The first indicator determines the short-term trend while the second indicator determines the long-term trend. Once the clarity over market movement is established, a myriad of entry techniques can be used to trade, with the help of the B-Xtrender. The following details both components of the system.

Figure 1. Daily chart of WALMART, with price plotted as candlesticks and the B-Xtrender components determining the short-term and long-term trends

The Short-Term Indicator

The short-term indicator indicates the *corrections* in the ongoing major trend.

The short-term indicator is constructed by using the following steps:

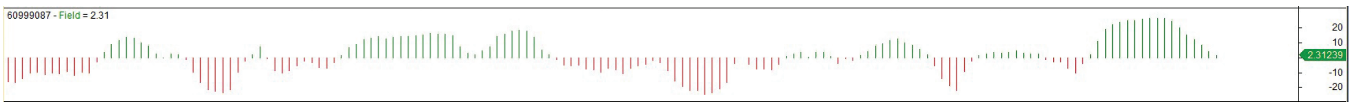
a. A 20-day exponential moving average of the price is derived. A 20-day period is selected, as it encompasses roughly a trading month. Exponential moving averages are one of the most dynamic ways of smoothing the trend.
b. The 15-day period RSI (Wilder's Relative Strength Index) of the above 20-day period EMA of Price is calculated.
c. The above formula is then plotted as a histogram for better visual representation.

We can use Amibroker Afl for the creation of the above:

Field = (RSIa((EMA(C,5)- EMA(C,20)),15))-50;

When the histogram is above zero, it indicates a short-term positivity in the markets. Similarly, when the histogram is below zero (red) it indicates a short-term negativity in the market.

Figure 2. Graphical representation of the short-term indicator plotted on DAX as on 2 January 2017. The green areas above zero represent short-term positivity, and the red areas represent short-term negativity.



The Long-Term Indicator

The long-term indicator displays the major trend that is in place. The long-term indicator is constructed by using the following steps:

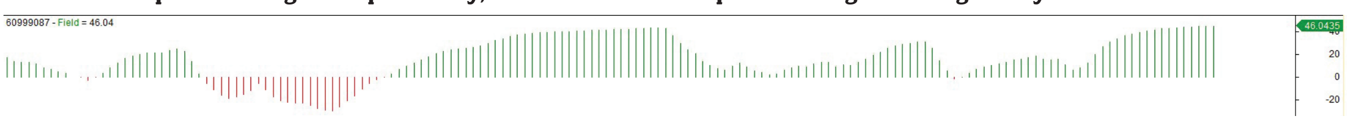
a. A 5-day exponential moving average of the closing price is derived. A 5-day period is selected, as it marks a trading week.
b. A 20-day exponential moving average of the closing price is derived. A 20-day period is considered, as it marks a trading month.
c. The difference of a 5-day exponential moving average of the price and a 20-day exponential moving average of the price is derived.
d. A 15-day period RSI (Wilder's Relative Strength Index) of the above "difference" is derived and plotted.
e. The above derivation is plotted as a histogram for better visual representation.

We can use Amibroker Afl to create the above formula as:

Field = (RSIa((EMA(C,5)- EMA(C,20)),15))-50

When the histogram is above zero, it turns green, indicating positivity in the long-term trend. Similarly, when the histogram is below zero, it turns red, indicating *negativity* in the long-term trend.

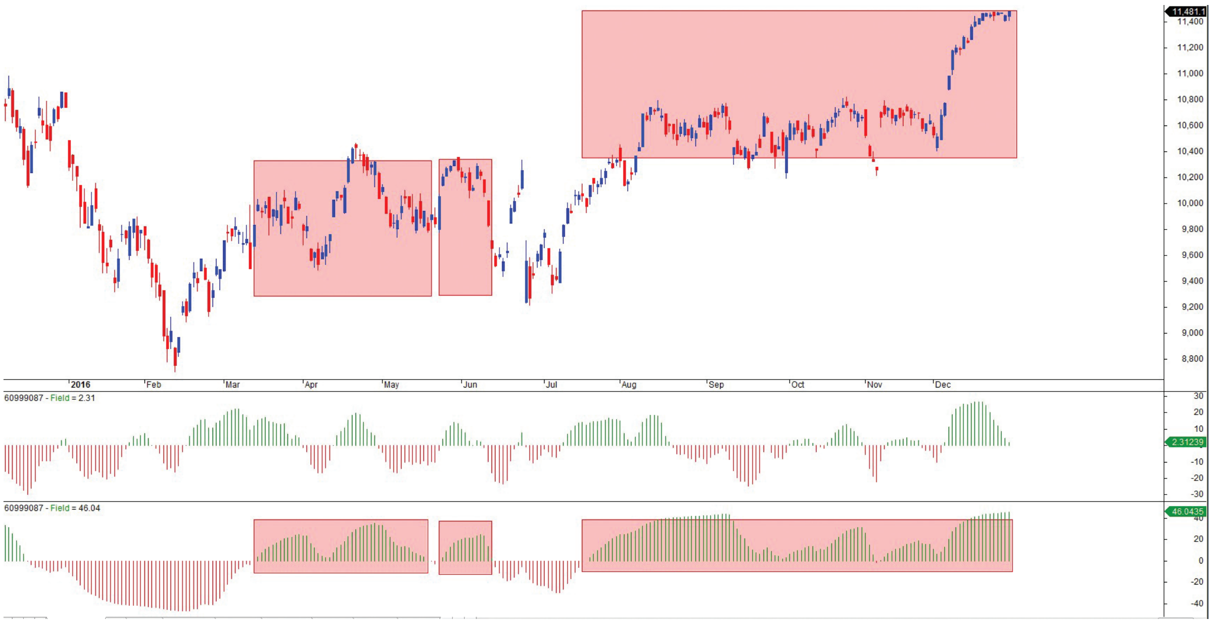
Figure 3. Graphical representation of the long-term indicator plotted on DAX as on 2 January 2017. The green areas above zero represent long-term positivity, and the red areas represent long-term negativity.



Results

Comparing Price and Long-Term Histogram

Figure 4. DAX daily data plotted for one year



In Figure 4, the lowest pane is the long-term histogram. We can see, as the long-term histogram stays green, the trend on DAX has remained positive. The long-term histogram ignores the daily blips in the trend and focuses on the long-term movement of the trend.

Similarly, the area on the long-term histogram that is red depicts a bearish trend in the DAX. Until mid-February 2016, a downtrend was prominent as prices were continuously falling. The histogram during that phase was red and below zero, indicating the prominence of the same. The bounces during this phase were completely ignored by the histogram. It kept its focus on the long-term trend.

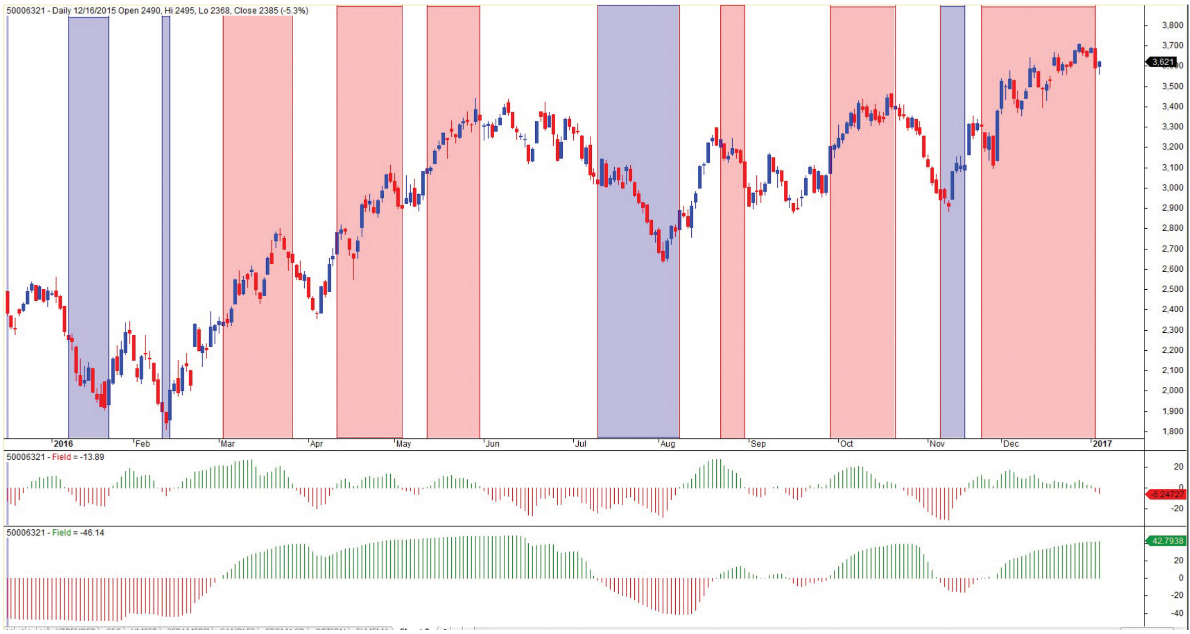
Comparing Price and Short-Term Histogram

Figure 5. DAX data plotted for one year

In Figure 5, the middle pane plots the short-term histogram. We can see that every time the trend moves up in the short term, the histogram turns green. The short-term histogram displays the medium-term positivity in the DAX, thereby keeping participants in line with the trend.

Bringing Long-Term and Short-Term Histograms Together

Figure 6. Price of Crude Oil listed on MCX



In Figure 6, the areas have been highlighted when both the long-term and short-term histogram show a trend in the same direction. The area marked in red shows the periods where both the histograms were positive (i.e., crude oil was positive in the shorter as well as longer trend). Similarly, the area marked in blue is the period where the crude oil was bearish in both timeframes.

From Figure 6, we can make the following interpretations:

a. We can use the B-Xtrender system for trading.
b. Positions can be created in the direction of the major trend (i.e., in the direction that the long-term histogram displays).
c. As the short-term histogram is more sensitive to prices, it will change its color frequently.
d. Initial entry in the trade can be taken, and then the long-term histogram changes color (either red to green or green to red). At this time, the short-term histogram is already in tandem with the long-term histogram.
e. Profits can be booked either wholly or partially when the short-term histogram changes color while the long-term histogram is intact. By doing this, we are saving our account from the damage that the correction can do to our positions.
f. Reentry in the position can be made when the short-term histogram is in tandem with the long-term histogram. In this way, we are taking advantage of the correction to add to our positions.
g. Exiting the whole position is desirable if the long-term histogram changes color (if during corrections, profits on all positions were not booked).

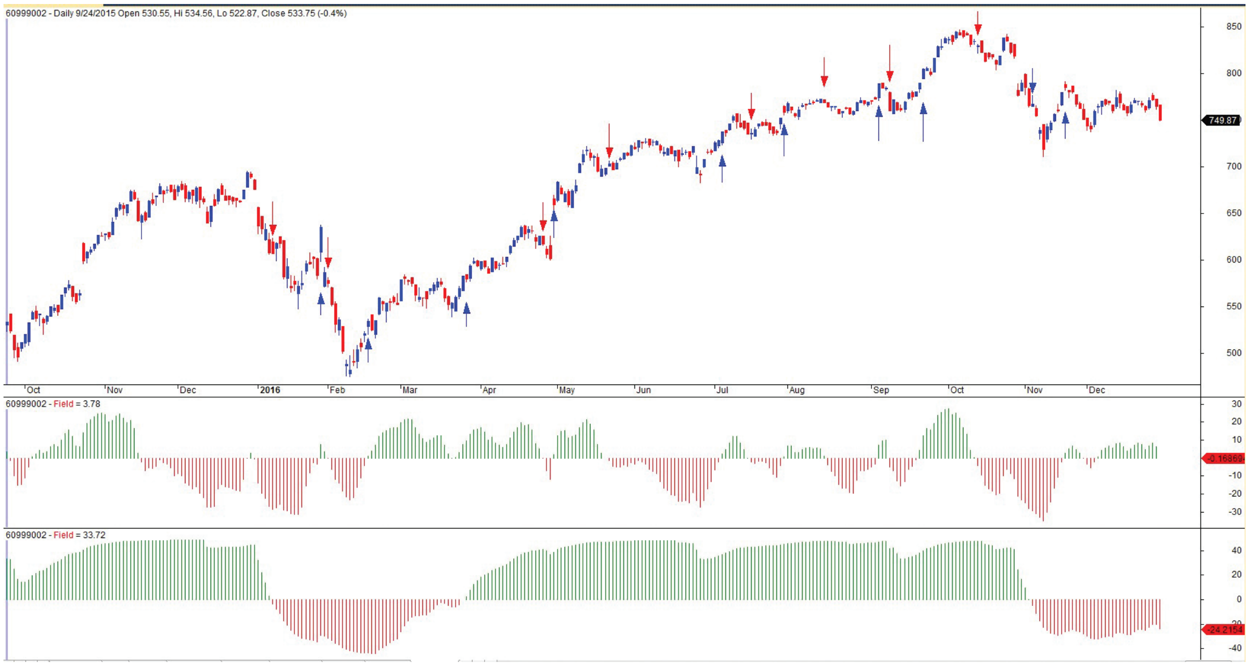
Table 1. Results derived on trading with the histogram on the same chart with the rules mentioned above

Date	Long Term Hisogram	Short Term Histogram	Entry	Date	Long Term Histogram	Short Term Histogram	Exit	Points
7/1/2016	Negative	Turns Negative	2254	22/1/2016	Negative	Turns Positive	2158	96
10/2/2016	Negative	Turns Negative	1899	15/2/2016	Negative	Turns Positive	2037	-138
3/2/2016	Turns Positive	Positive	2341	29/3/2016	Positive	Turns Negative	2562	221
12/4/2016	Positive	Turns Positive	2782	4/5/2016	Positive	Turns Negative	2901	119
12/5/2016	Positive	Turns Positive	3096	1/6/2016	Positive	Turns Negative	3308	212
7/11/2016	Turns Negative	Negative	3019	8/8/22016	Negative	Turns Positive	2891	128
22/8/2016	Turns Positive	Positive	3212	1/9/2016	Positive	Turns Negative	2909	-303
29/9/2016	Turns Positive	Positive	3204	24/10/2016	Positive	Turns Negative	3355	151
4/11/2016	Turns Negative	Negative	2940	21/11/2016	Negative	Turns Positive	3315	-375
24/11/201	Turns Positive	Positive	3303	3/1/2017	Positive	Turns Negative	3590	287
								398

Conclusions of the test:

a. 398 points were made during the year.
b. Vanilla histogram method is used for entries and exits.
c. No stop-loss methods are added.
d. No position sizing is involved.

Figure 7. Daily chart of AMAZON Co.



As shown in Figure 7, in applying the B-Xtrender entry and exit methods on the market for one year, we got the following results. The blue arrows below the candles are buy points, and the red arrows above the price candles are the sell points.

Table 2. Total points made during the year

Date	Long Term Hisogram	Short Term Histogram	Entry	Date	Long Term Histogram	Short Term Histogram	Exit	Points
8/1/2016	Turns Negative	Negative	607.05	28/1/2016	Negative	Turns Positive	587	20.05
1/2/2016	Negative	Turns Negative	574.81	17/2/2016	Negative	Turns Positive	534.1	40.71
28/3/2016	Turns Positive	Positive	579.87	26/4/2016	Positive	Turns Negative	616.88	37.01
29/4/2016	Positive	Turns Positive	659.59	20/5/2016	Positive	Turns Negative	702.8	43.21
6/7/2016	Positive	Turns Positive	737.61	18/7/2016	Positive	Turns Negative	736.07	-1.54
29/7/2016	Positive	Turns Positive	758.81	16/8/2016	Positive	Turns Negative	764.04	5.23
6/9/2016	Positive	Turns Positive	788.87	9/9/2016	Positive	Turns Negative	760.14	-28.73
21/9/2016	Positive	Turns Positive	789.74	13/10/2016	Positive	Turns Negative	829.28	39.54
3/11/2016	Turns Negative	Negative	767.03	22/11/2016	Negative	Turns Positive	785.33	-18.3
					Total Points Made during the year			137.18

$137.18 points were made per one share.

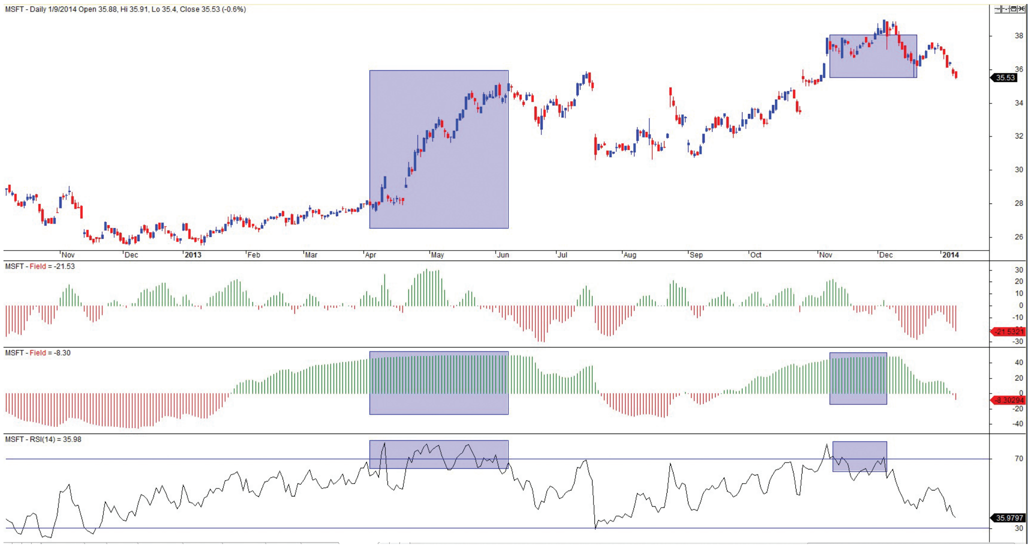
Discussion

Overbought and Oversold

The biggest challenge that a trader faces while using an overbought/oversold technical indicator is that the indicator signals the exit from a trend too early. Also, indicators tend to remain oversold and give buy signals even when the markets keep making new lows.

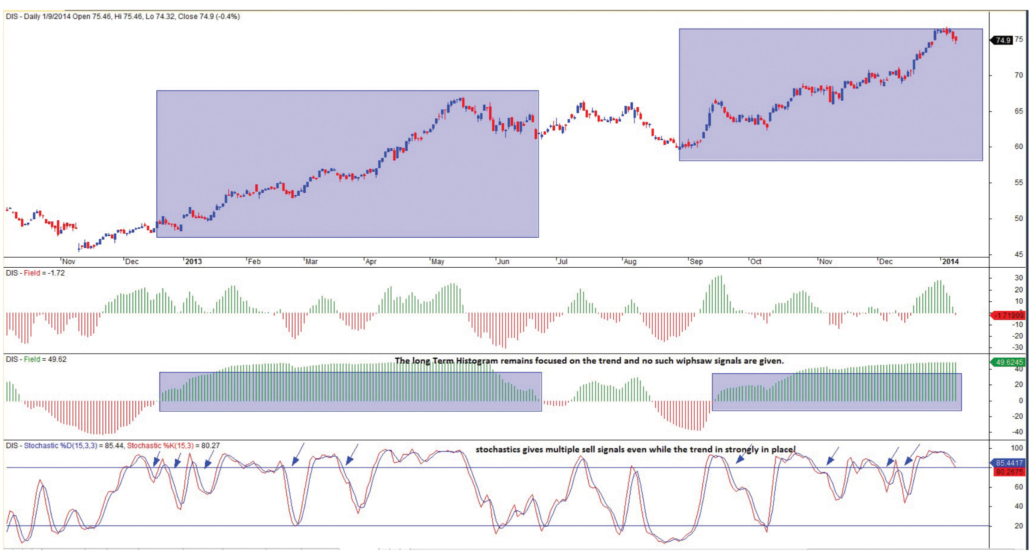
Similarly, indicators tend to become oversold and give sell signals even though the markets keep making new highs, whereas B-Xtrender tends to remain in the direction of the trend and avoid any false signals during corrections.

Figure 8. Data of Microsoft



In Figure 8, a comparison with RSI is made. In the middle of the chart, we see that RSI becomes oversold multiple times, giving sell signals, whereas the trend had just begun its journey northwards. Following the RSI would have caused early exit and whipsaws in the trend. Traders would not have been able to extract the benefits from it. The long-term histogram (i.e., the trend indicator) turned green from the trend initialization and didn't give any signs of the trend weakness unless the trend remained in force. A similar situation is evident on the right-hand side of the chart.

Figure 9. Walt Disney daily



In Figure 9, we compare the long-term histogram with the stochastics. From mid-December 2012 to mid-June 2013, the stochastic gave a sell signal multiple times. In fact, the stochastics have shown sell every time the prices were making new highs. The correction phase in the trend is not identified, and a sell signal is generated. In the long-term histogram, right from the beginning of the trend until the end, no sell signal was generated. The histogram was well above zero levels in green, showing that the trend was still in force, and the sell signals generated by stochastics were just a mere blip in the ongoing trend. Similarly, from mid-September 2015 until the end of the chart, Walt Disney was in uptrend. The stochastics gave various sell signals, whereas the long-term histogram is focused on the major trend.

Testing the Results of B-Xtrender Vanilla Buy—Sell Trades

Now let's test the results of the B-Xtrender histogram buy—sell.

We take the results of Table 2 and assume that $100 was initially introduced, and all trades are done in single unit. Also, please note no position sizing and stop-loss methods are involved. The holistic nature of the system is such that traders can apply their own position sizing and stop-loss methods. The B-Xtrender presents a simplistic trading view.

Table 3. Total points made during the year, with profit and loss added

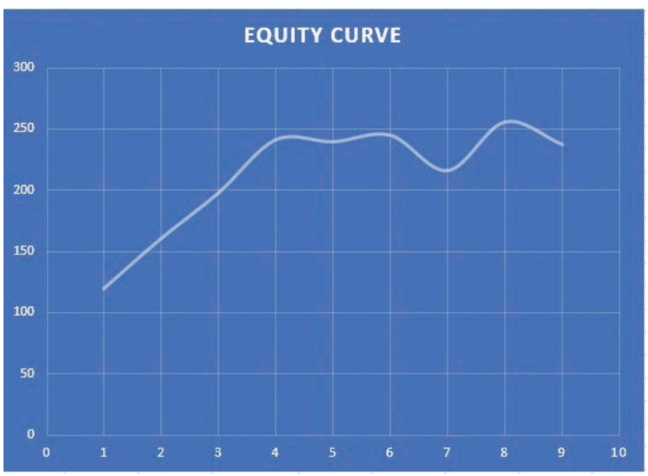
Date	Long Term Hisogram	Short Term Histogram	Entry	Date	Long Term Histogram	Short Term Histogram	Exit	Points	P/L
8/1/2016	Turns Negative	Negative	607.05	28/1/2016	Negative	Turns Positive	587	20.05	120.05
1/2/2016	Negative	Turns Negative	574.81	17/2/2016	Negative	Turns Positive	534.1	40.71	160.76
28/3/2016	Turns Positive	Positive	579.87	26/4/2016	Positive	Turns Negative	616.88	37.01	197.77
29/4/2016	Positive	Turns Positive	659.59	20/5/2016	Positive	Turns Negative	702.8	43.21	240.98
6/7/2016	Positive	Turns Positive	737.61	18/7/2016	Positive	Turns Negative	736.07	-1.54	239.44
29/7/2016	Positive	Turns Positive	758.81	16/8/2016	Positive	Turns Negative	764.04	5.23	244.67
6/9/2016	Positive	Turns Positive	788.87	9/9/2016	Positive	Turns Negative	760.14	-28.73	215.94
21/9/2016	Positive	Turns Positive	789.74	13/10/2016	Positive	Turns Negative	829.28	39.54	255.48
3/11/2016	Turns Negative	Negative	767.03	22/11/2016	Negative	Turns Positive	785.33	-18.3	237.18
					Total Points Made during the year			137.18	

In Table 3, which adds a column for profit and loss, we assume initial investment of $100 in the margin account, and all trades are done in a single unit. At the end of the year we see total profit and loss account stands at $237.18.

The system's performance parameters:

a. *Equity Curve:* The equity curve gives us the initial signal that the system we are testing may be profitable. Figure 10 gives the equity curve for one year for the buy–sell histogram vanilla strategy. It can be seen that this system's equity curve tends to continuously create new peaks. It means that after periods of losses (drawdowns) the trading system has the power to create new price peaks again (i.e., to enter into a series of profitable trades).

Figure 10. Equity curve for one year for the buy–sell histogram vanilla strategy



b. *Total Net Profits:* Net profit is the sum of all winning (gross profit) and losing (gross loss) trades. Its value can be both positive and negative.

It is seen that the total net profit stands as follows:

Total Profit/Loss Account 237.18
Less: Initial Investment 100.00
Total Profit for the Year 137.18

c. *Drawdown:* Drawdown is the difference between the historical peak of our equity curve and the subsequent cumulative price decline. It does not necessarily mean a loss; it may be only a price collapse. It can be expressed as the amount of money or percentage of the largest cumulative decline in capital in our historical trades or back tests. Its value or a multiple of its value are often used to determine the size of the account for live trading in a particular market and to determine the maximum acceptable risk and stop-loss before we start to trade live.

The historic peak of the equity curve was at 240.98, and the subsequent low was at 215.94. The maximum historical drawdown in this particular market is 25.04. We can say our trading strategy requires an account with at least triple drawdown value (i.e., 25.04*3 = 75.12). Note, we have started with $100; if we had started with $75.12, the performance would have been enhanced.

d. *Profit Factor:* Profit factor is the ratio of all winning (gross profit) and losing (gross loss) trades. Its lowest value is 0, and the highest value is not limited. A profit factor of 2.5 is considered a standard value for testing a system.

In our example:
Gross Profit = 20.5+40.71+37.01+43.21+5.23+39.54
= 186.2
Gross Loss = 48.57
Gross Profit = 137.63
Profit Factor = Gross Profit/Gross Loss
186.20/48.57
= 10.02

e. *Percentile Profitable:* If we take the number of winning trades and divide it by the total number of trades and then multiply the result by 100, we get the percentage of successful trades. The question is, to what extent is this a decisive indicator for us?

Total number of trades = 9
Total number of profitable trades = 6
Profit Percentile = (6/9) * 100
= 66.66%

That also indicates only 1/3 of the total trades were loss making.

f. *Average profit/loss per one trade (average trade net profit):* This indicator can give us a lot of useful information in trading. Its calculation is very simple—it is the arithmetic average of all trades (i.e., both the winning and losing ones). It can be both positive and negative. If the indicator's value is positive, it means that the overall back-testing result was a profit. If the value is negative, the back-testing showed that the strategy brought a loss.

Table 4. Sum of profit and loss points

Date	Points
8/1/2016	20.05
1/2/2016	40.71
28/3/2016	37.01
29/4/2016	43.21
6/7/2016	-1.54
29/7/2016	5.23
6/9/2016	-28.73
21/9/2016	39.54
3/11/2016	-18.3
	137.18

The mean of the above results is calculated as follows:

Sum of profit and loss points = 137.18

Total number of trades = 9

The mean of all the trades = 137.18/9

= 15.24

These six steps give an overview of the entire process of building a trading system.

To test the system further using more advanced parameters, the following code was derived and run on contracts for a longer period.

```
ShortTerm = (RSIa((EMA(C ,5)- EMA(C ,20)),15))-50;
LongTerm = (RSIa(EMA(C, 20),15))-50;

PosChangeInLongTerm = ((Ref(LongTerm,-1)<0) AND (LongTerm > 0));
NegChangeInLongTerm = ((Ref(LongTerm,-1)>0) AND (LongTerm < 0));
PosChangeInShortTerm = ((Ref(ShortTerm,-1)<0) AND (ShortTerm > 0));
NegChangeInShortTerm = ((Ref(ShortTerm,-1)>0) AND (ShortTerm < 0));

ChangeInLongTerm = PosChangeInLongTerm OR NegChangeInLongTerm;
ChangeInShortTerm = PosChangeInShortTerm OR NegChangeInShortTerm;
/*
if (Option == "1"){
      Field = ShortTerm;
}
else{
      Field = LongTerm;
}
if (Style == "Histogram")
      Plot (Field,"Field",IIf(Field>0,colorGreen,colorRed),styleHistogram);
else
      Plot (Field+50,"Field",IIf(Field>0,colorGreen,colorRed),styleThick);

Plot(MA(Field+50,20),"MAofBExtender",colorBlue,styleThick);
if (explorer == "LT"){
      Filter = ChangeInLongTerm;
      AddColumn(PosChangeInLongTerm,"Positive");
      AddColumn(NegChangeInLongTerm,"Negative");
}
else if (explorer == "ST"){
      Filter = ChangeInShortTerm;
      AddColumn(PosChangeInShortTerm,"Positive");
      AddColumn(NegChangeInShortTerm,"Negative");
}
*/
InitialBuy = PosChangeInLongTerm;
InitialSell = NegChangeInLongTerm;

Buy = InitialBuy OR ((LongTerm > 0) AND PosChangeInShortTerm);
Sell = (LongTerm > 0) AND NegChangeInShortTerm;
Short = InitialSell OR ((LongTerm < 0) AND NegChangeInShortTerm);
Cover = (LongTerm <0) AND PosChangeInShortTerm;
//if (explorer == "Trades"){
      Filter = Buy OR Sell OR Short OR Cover;
      AddTextColumn( FullName(), "Company Name", 1.7, colorDefault, ( IIf( Buy OR Cover, colorGreen,
colorRed ) ) );
      AddColumn(Buy,"Buy");
      //AddColumn(Sell,"Sell");
      AddColumn(Short,"Short");
      //AddColumn(Cover,"Cover");
//}

Plot(0,"",colorRed,styleThick);
_ SECTION _ END();
```

Parameters and Tests for the Strategy for a Longer Period of Time

The trading strategy (mentioned earlier) was tested on the following parameters:

1) Profit Distribution
2) Maximum Adverse Excursion Distribution
3) Maximum Favorable Excursion Distribution
4) Minimum 10 Years Historical End on Day Data

Monte Carlo Simulation for all the trades has been provided.

The following contracts were chosen for performing the above tests:

GOLD — Futures, listed on MCX (India)

STARBUCKS — Stock

The above have been picked, as these two symbolize two different contract segments: commodities and stocks.

GOLD — MCX

Statistics				
	All trades	Long trades	Short trades	Buy&Hold (50006325)
Initial capital	1000000.00	1000000.00	1000000.00	1000000.00
Ending capital	2048342.51	2342201.03	706141.48	4863794.51
Net Profit	1048342.51	1342201.03	-293858.52	3863794.51
Net Profit %	104.83%	134.22%	-29.39%	386.38%
Exposure %	56.70%	34.84%	21.86%	100.00%
Net Risk Adjusted Return %	184.89%	385.29%	-134.40%	386.38%
Annual Return %	5.38%	6.42%	-2.51%	12.25%
Risk Adjusted Return %	9.49%	18.42%	-11.48%	12.25%
Total transaction costs	0.00	0.00	0.00	0.00
All trades	207	122 (58.94 %)	85 (41.06 %)	1
Avg. Profit/Loss	5064.46	11001.65	-3457.16	3863794.47
Avg. Profit/Loss %	0.41%	0.78%	-0.12%	386.38%
Avg. Bars Held	11.87	12.34	11.21	3971.00
Winners	76 (36.71 %)	48 (23.19 %)	28 (13.53 %)	1 (100.00 %)
Total Profit	4443276.39	3104277.51	1338998.89	3863794.47
Avg. Profit	58464.16	64672.45	47821.39	3863794.47
Avg. Profit %	3.59%	4.03%	2.85%	386.38%
Avg. Bars Held	20.29	20.77	19.46	3971.00
Max. Consecutive	8	6	3	1
Largest win	352920.23	352920.23	158813.10	3863794.47
# bars in largest win	46	46	32	3971
Losers	131 (63.29 %)	74 (35.75 %)	57 (27.54 %)	0 (0.00 %)
Total Loss	-3394933.89	-1762076.47	-1632857.41	0.00
Avg. Loss	-25915.53	-23811.84	-28646.62	N/A
Avg. Loss %	-1.44%	-1.33%	-1.58%	N/A
Avg. Bars Held	6.99	6.86	7.16	N/A
Max. Consecutive	9	7	11	0
Largest loss	-94659.83	-94659.83	-67772.70	0.00
# bars in largest loss	4	4	5	0
Max. trade drawdown	-144979.37	-144979.37	-97529.24	-1696316.96
Max. trade % drawdown	-6.45	-6.45	-4.84	-28.35
Max. system drawdown	-576022.49	-622738.80	-756869.83	-1696316.96
Max. system % drawdown	-25.62%	-23.24%	-62.61%	-28.35%
Recovery Factor	1.82	2.16	-0.39	2.28
CAR/MaxDD	0.21	0.28	-0.04	0.43
RAR/MaxDD	0.37	0.79	-0.18	0.43
Profit Factor	1.31	1.76	0.82	N/A
Payoff Ratio	2.26	2.72	1.67	N/A
Standard Error	185860.93	160733.05	100637.60	515434.56
Risk-Reward Ratio	0.34	0.68	-0.45	0.74
Ulcer Index	10.80	8.84	32.80	11.69
Ulcer Performance Index	-0.00	0.11	-0.24	0.59
Sharpe Ratio of trades	0.28	0.66	-0.64	N/A
K-Ratio	0.02	0.04	-0.03	0.05

Figure 11. Profit distribution chart

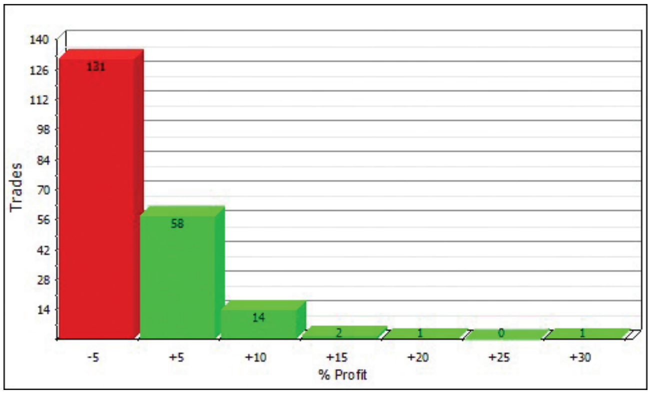
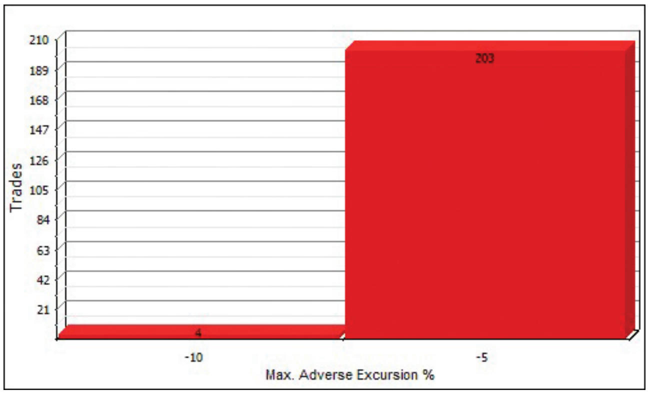


Figure 12. Maximum adverse excursion distribution



Monte Carlo					
Percentile	Final Equity	Annual Return	Max. Drawdown $	Max. Drawdown %	Lowest Eq.
1%	0	-100.00%	-1317032	-100.00%	0
5%	655734	-3.04%	-1000000	-81.28%	208824
10%	966029	-0.25%	-859980	-65.58%	398119
25%	1492572	2.97%	-679813	-47.19%	637248
50%	2028524	5.30%	-515812	-32.24%	832005
75%	2568406	7.14%	-407736	-23.69%	935564
90%	3140442	8.72%	-341624	-17.94%	991029
95%	3432662	9.43%	-298155	-15.44%	1000000
99%	4115822	10.89%	-250982	-11.94%	1000000

Figure 13. Maximum favorable excursion distribution

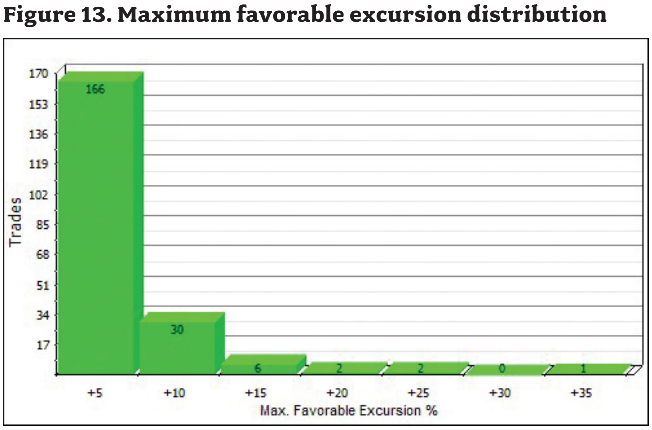


Figure 14. MC minimum/maximum equity

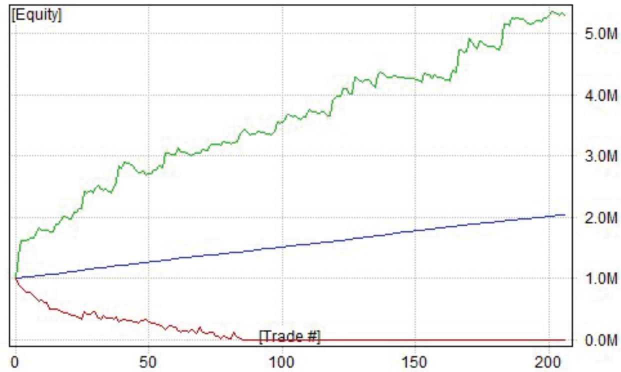


Figure 15. MC final equity

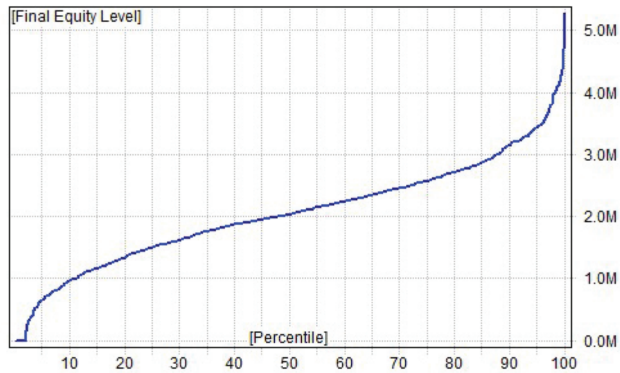


Figure 16. MC annual profit %

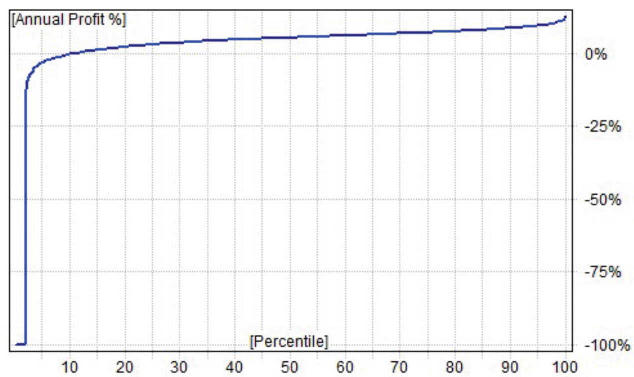


Figure 17. MC drawdown %

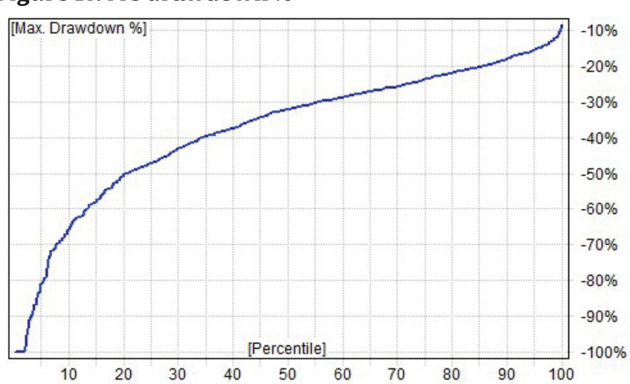


Figure 18. MC drawdown $

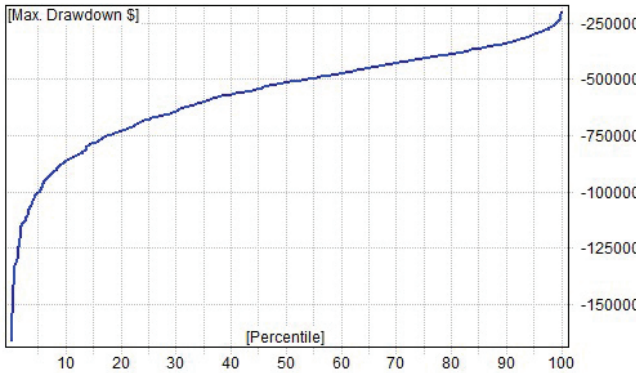
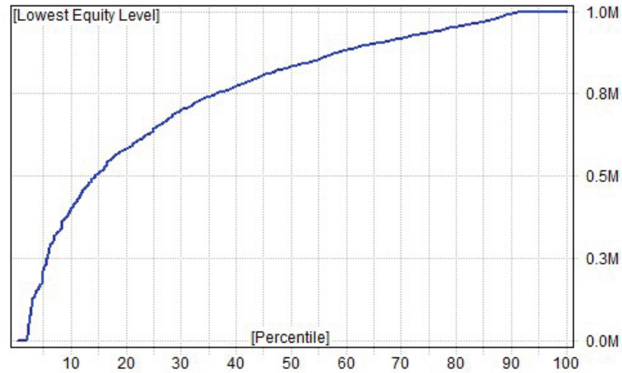


Figure 19. MC lowest equity



The above tests were carried out with the following additional settings:

Settings			
Initial Equity:	1000000	Periodicity/Positions:	Daily/Long Short
Commissions:	0.00 (Use portfolio settings)	Annual interest rate:	0.00%
Range:	All quotations	Apply to:	Current Symbol
Account margin:	100	Futures mode:	No
Def. round lot size:	0	Def. Tick Size	0
Drawdowns based on:	High/Low prices		
Long trades			
Buy price:	Close	Sell price:	Close
Buy delay:	0	Sell delay:	0
Short trades			
Short price:	Close	Cover price:	Close
Short delay:	0	Cover delay:	0
Stops			
Maximum loss:	disabled	Profit target:	disabled
Value:	1.00	Value:	0.00
Exit at stop?	no	Exit at stop?	no
Trailing stop:	disabled		
Value:	2.00		
Exit at stop?	no		

Parameters:

Name	**Value**
Stop Loss (times ADR)	1.5
Target-2 (times ADR)	1.5
Delta	5
Include CCI	No
Reversal/Divergence	Reversal
Include Bounce	Yes
Target-1 (times ADR)	1.5

Running the above tests on STARBUCKS:

Statistics				
	All trades	**Long trades**	**Short trades**	**Buy&Hold (60990865)**
Initial capital	1000000.00	1000000.00	1000000.00	1000000.00
Ending capital	726825.38	1198005.99	528819.39	174906984.42
Net Profit	-273174.62	198005.99	-471180.61	173906984.42
Net Profit %	-27.32%	19.80%	-47.12%	17390.70%
Exposure %	13.59%	7.76%	5.83%	100.00%
Net Risk Adjusted Return %	-200.98%	255.14%	-807.99%	17390.70%
Annual Return %	-1.26%	0.72%	-2.51%	22.88%
Risk Adjusted Return %	-9.31%	9.32%	-43.04%	22.88%
Total transaction costs	0.00	0.00	0.00	0.00
All trades	353	212 (60.06 %)	141 (39.94 %)	1
Avg. Profit/Loss	-773.87	933.99	-3341.71	173906984.44
Avg. Profit/Loss %	-0.29%	0.48%	-1.44%	17390.70%
Avg. Bars Held	10.88	11.14	10.48	6309.00
Winners	109 (30.88 %)	74 (20.96 %)	35 (9.92 %)	1 (100.00 %)
Total Profit	1444834.71	926236.21	518598.51	173906984.44
Avg. Profit	13255.36	12516.71	14817.10	173906984.44
Avg. Profit %	7.28%	7.33%	7.18%	17390.70%
Avg. Bars Held	18.97	19.20	18.49	6309.00
Max. Consecutive	4	3	2	1
Largest win	117999.73	117999.73	74082.31	173906984.44
# bars in largest win	27	27	17	6309
Losers	244 (69.12 %)	138 (39.09 %)	106 (30.03 %)	0 (0.00 %)
Total Loss	-1718009.33	-728230.22	-989779.12	0.00
Avg. Loss	-7041.02	-5277.03	-9337.54	N/A
Avg. Loss %	-3.67%	-3.19%	-4.29%	N/A
Avg. Bars Held	7.26	6.82	7.83	N/A
Max. Consecutive	9	11	16	0
Largest loss	-83007.94	-29658.33	-83007.94	0.00
# bars in largest loss	7	8	7	0
Max. trade drawdown	-90870.83	-39923.19	-90870.83	-48310761.71
Max. trade % drawdown	-18.42	-16.80	-18.42	-81.91
Max. system drawdown	-441058.92	-117322.77	-637922.89	-48310761.71
Max. system % drawdown	-38.52%	-11.47%	-54.95%	-81.91%
Recovery Factor	-0.62	1.69	-0.74	3.60
CAR/MaxDD	-0.03	0.06	-0.05	0.28
RAR/MaxDD	-0.24	0.81	-0.78	0.28
Profit Factor	0.84	1.27	0.52	N/A
Payoff Ratio	1.88	2.37	1.59	N/A
Standard Error	69076.38	53019.38	106974.63	26652595.84
Risk-Reward Ratio	-0.06	0.10	-0.09	0.22
Ulcer Index	13.59	4.38	17.90	23.94
Ulcer Performance Index	-0.49	-1.07	-0.44	0.73
Sharpe Ratio of trades	-0.36	0.19	-1.24	N/A
K-Ratio	-0.01	0.01	-0.01	0.02

Figure 20. Profit distribution

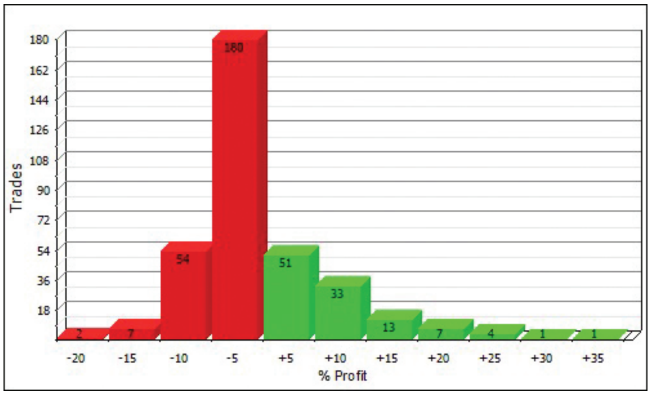


Figure 21. Maximum adverse excursion distribution

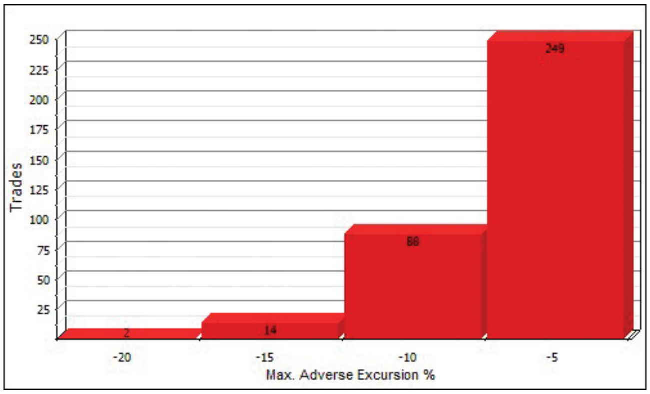


Figure 22. Maximum favorable excursion distribution

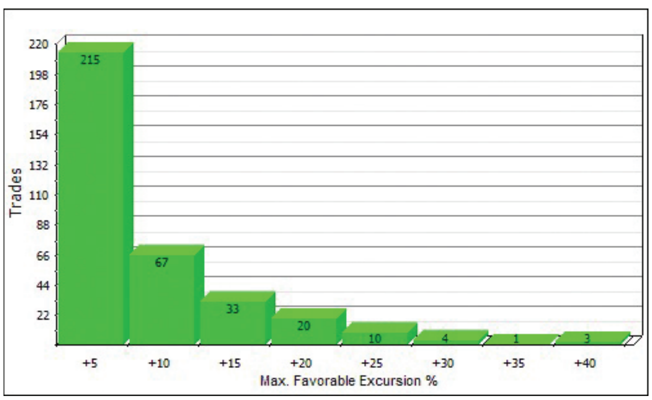


Figure 23. MC minimum/maximum equity

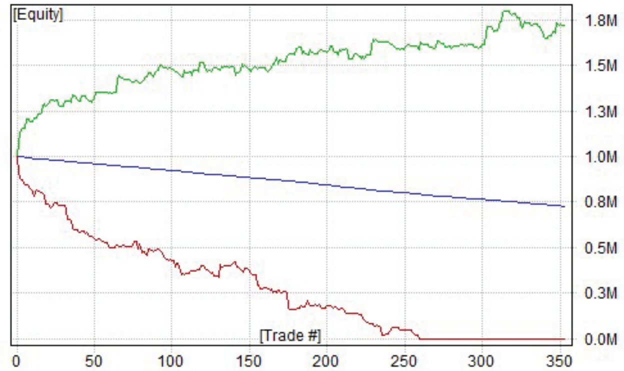


Figure 24. MC final equity

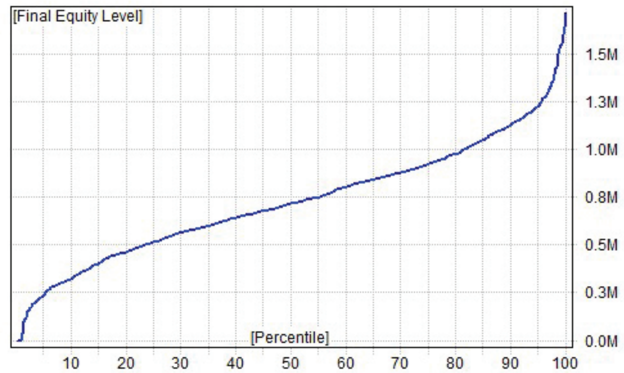
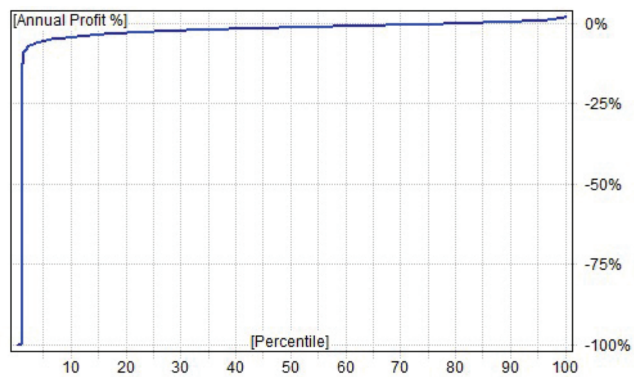


Figure 25. MC annual profit %



Monte Carlo					
Percentile	**Final Equity**	**Annual Return**	**Max. Drawdown $**	**Max. Drawdown %**	**Lowest Eq.**
1%	0	-100.00%	-1000000	-100.00%	0
5%	235881	-5.60%	-859750	-80.94%	196352
10%	318859	-4.46%	-771004	-73.40%	277684
25%	512610	-2.63%	-624251	-58.33%	445608
50%	715108	-1.33%	-475648	-43.21%	614113
75%	922130	-0.32%	-340193	-30.62%	770889
90%	1129970	0.49%	-249007	-21.82%	884315
95%	1226350	0.82%	-209993	-17.52%	936172
99%	1526336	1.70%	-162735	-12.61%	986312

Figure 26. MC drawdown %

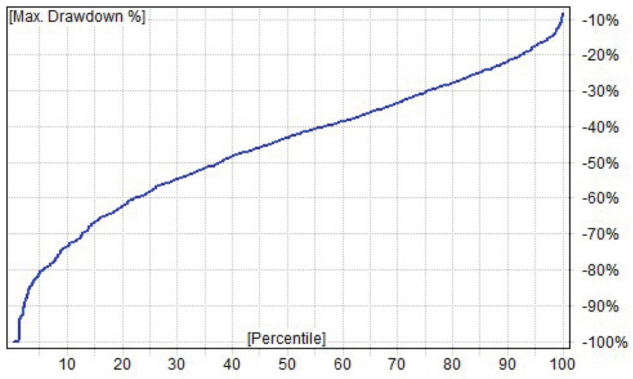


Figure 27. MC drawdown $

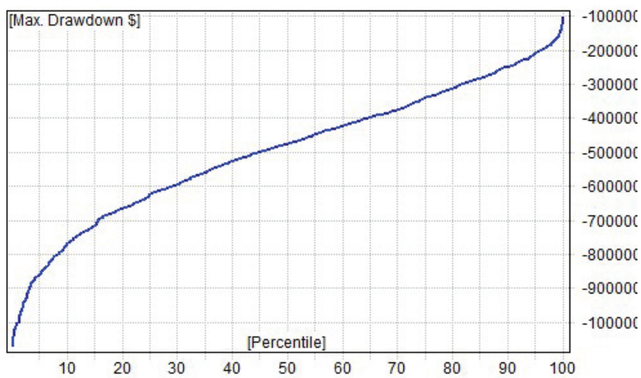
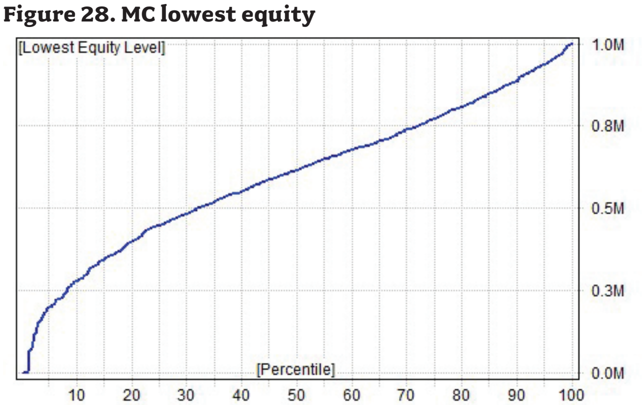


Figure 28. MC lowest equity



Conclusion

It is common knowledge that a trend remains in force until it bends, and every trend-following trader speculates to enter at the right time in an ongoing trend. The real dilemma faced by each trend-following trader is when to book partial profits versus when to exit the trade or reverse the open positions.

A trader takes advantage of the many available trend-following tools, with those indicating overbought and oversold levels being the most commonly used. Any technical analysis software worth its name has an arsenal of indicators.

One commonly observed downside of the existing indicators is that when a strong trend is in progress, the indicator tends to give the early signals without providing any indications to scale up or down, as the case may be.

Another often met challenge in using the existing indicators is that they do not give the trader any clue whether the ongoing correction in a trend is just a blip correction or the major trend is undergoing a change.

The most commonly used indicators also seem to present a myopic vision of the trend, thus tending to ignore the major trend and falling into the minor trap.

B-Xtrender is plotted in a single window and gives a view of the intermediate and major trend in a single glance. It attempts to provide precise entries, exits, and scaling (up or down) signals. It also successfully recognizes and differentiates between a short-term correction and a trend change, thereby guiding the trader to book profits or exit at the suitable time. It can be used as a standalone system, using price action, to trade markets of all spectra.

References

Wilder, J. Welles (1978): *New Concepts in Technical Trading Systems.*

Software

All charts are Amibroker based. The formulas are written in Amibroker AFL language.

Momentum Based Techniques Combined With Relative Trends in Sectors Rotation

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Abstract

The role of today's market technician is more and more oriented toward the optimization of the investment process in global asset allocation. The purpose of this paper is to define a systematic approach for a dynamic allocation in the stock market by employing financial instruments representing the main economic sectors.

A huge contribution to the algorithmic analysis is given by momentum based techniques as a basic component of quantitative allocation models: this study introduces a methodology for obtaining a risk-controlled portfolio by combining ETFs on equities sectors through a bottom-up selection based on trend-following techniques. The risk optimization factors in portfolio construction can be improved through a trend-based variable exposure and multiple weighting criteria.

Introduction

This study intends to provide the guidelines for a portfolio strategy to be implemented by a diversification among the stock indexes representing the most relevant economic sectors that can be replicated by employing Exchange Traded Funds.

A diversified passive portfolio in equities can be rewarding over the long run, but the risk of large capital drawdowns, which are notoriously severe when a cyclical bear market occurs, is a big concern for the average investor.

Trend detection is a basic tenet of technical analysis: a trend following strategy is the most effective tool an investor can rely on in adverse conditions since it allows one to reduce, or even set to zero, the investment exposure in equities during unfavorable market phases. We cannot get out of a trend at the best point, but over the long run, a trend strategy can dramatically improve the quality of returns in terms of reward/risk ratios.

The methodology here proposes a solution to the problem through a long-only dynamic exposure in world stocks by detecting trends in single sectors and changing the investment weightings accordingly. Multiple techniques can be combined into a single portfolio strategy (e.g., an index to determine the weighted exposure to the market according to a bottom-up selection based on the single trends of the specific sector indices; a sub-selection among the relatively strongest sectors ranked by momentum; a trend-direction filter for altering the exposure to the market according to the sectors' participation to the global trend).

There are several ways to identify a trend; momentum is among the best techniques since it allows for the comparison of various degrees of strength among different asset classes. The Rate of Change (ROC) indicator is very simple but effective because it measures the percent change in price with the price *n* periods ago. This simple but sound concept allows one to determine both relative and absolute trends. Positive values for ROC reveal an uptrend, while comparing relative values for ROC helps to determine if a market instrument tends to be stronger or weaker than another. (Gary Edwin Anderson, The Janus Factor, Wiley 2012).

Materials and Methods

Investment Universe

The world markets universe is classified into different sectors according to two main standards: Global Industry Classification Standard (GICS) and Industry Classification Benchmark (ICB). The classification includes 11 sectors at the top level (10 until August 2016, when Real Estate was added). This study analyzes data until 2016, so it does not include Real Estate.

Ten ETFs have been considered in this study; historical data date back to September 2006 (with only a few since 2001). An additional back-testing has been made on the related benchmarks MSCI® ACWI Sectors Indexes to prove the method's robustness through a deeper historical database dating back to 1999 (See Table 1). The price indexes (excluding dividend) have been tested rather than the net return indexes (capitalized dividends) because of the related tracker ETFs that generally distribute dividends twice per year.

Table 1. Ten Global Sectors and ETFs Quoted in U.S. Dollars

MSCI® ACWI Sector Indexes	ETF i Shares® Global
Consumer Discretionary	RXI
Consumer Staples	KXI
Energy	IXC
Financials	IXG
Health Care	IXJ
Industrials	EXI
Information Technology	IXN
Materials	MXI
Telecommunication Services	IXP
Utilities	JXI
Real Estate (recent addition)	RWO (SPDR-DJ® Global Real Est)

Calculating EWI, Equal Sectors Weighting Index

The Morgan Stanley World Index is value weighted: the weights of its components depend on their total market capitalization, so the larger components weigh much more than the smaller ones. An equally weighted version of the index would not resolve the problem since there are also huge differences in the numbers of companies that belong to each sector. To obtain an equilibrated sectors distribution, this study considers as a benchmark, an index that equally weights the sector indexes that contribute to its composition.

The weekly returns of the Equal Weighted Index are calculated as follows:

$$EWI_t = EWI_{t-1} + EWI_{t-1} \times \left(\sum_{n=1}^{n} (S_t \div S_{t-1}) - 1 \right) \div n$$

Where :

EWI_t = current weekly close of the index

EWI_{t-1} = former weekly close of the index

S_t = current weekly close of each sector index

S_{t-1} = former weekly close of each sector index

n = number of sector indexes

Figure 1. MSCI® World (blue line) Compared With Equal Sectors Weighting 2000—2016 (red line)

Defining a momentum based investment methodology

Rates of change at 8, 13 and 26 weeks are calculated for each sector index according to the traditional method:

ROC = ($C_w \div C_{w-1}$) - 1

Where C_w is the last close for the week and C_{w-1} is the close of one week ago.

Strategy 1: At the end of each month (the last weekly close of the month, as we are working on weekly data), sum up the number of sectors that have a positive rate of change at 26 weeks. The result is a number between 0 and 10, since we consider a universe made of 10 sectors. This number is then divided by the number of sectors (10 in our case). The percentage value of this number indicates the global exposure attributed to this strategy. Each sector weights equally, but the whole exposure in this allocation segment corresponds to the number obtained in Strategy 1. For example, if the global exposure is 70%, 7% is attributed to each of the ten sectors.

Strategy 2: Calculate the best trending sector by ranking the values of the average among the rates of change at 8, 13 and 26 weeks for each sector. At the end of the last week of each month, attribute an equal weight to the sectors showing the highest ranking and then multiply it by the global exposure weighting calculated in Strategy 1. For example, if 20% is attributed to each sector (100% 5 = 20%) and the global exposure is 60%, then 12% will be allocated to each sector (12% x 5 = 60%)

Strategy 3: At the end of each month, each of the best five trending sectors calculated as in Strategy 2 is selected, but only if its average rate of change is positive. If negative, its stake will be maintained in cash. If, for example, only three out of the five relatively stronger sectors show a positive average rate of change, then a 60% exposure is attributed to this strategy (5 sectors x 20% = 100%, only three positively trending sectors x 20% = 60%).

A summary of the rules described above is shown in Table 2.

Table 2. Summary of Three Strategy Rules

Defining a Momentum Based Investment Methodology in 10 Global Equities Sectors	
Steps	**Procedures**
Composite RoC calculation	Calculate Rates of Change at 8, 13, 26 weeks for each sector index
Strategy 1:	At the end of each month, sum up the number of sectors which rate of change at 26 weeks is positive.
Trend Adjusted Equal Weight of 10 Sectors	Divide the resulting number by 10 (number of sectors). This is the percentage investment exposure to the strategy. Each sector weights equally, but the whole exposure in this allocation segment corresponds to the number obtained. For example, if the global exposure is 70%, a 7% is attributed to each of the ten sectors.
Strategy 2:	Calculate the best trending sectors by ranking 1 to 10 the values of the average of the rates of change at 8, 13 and 26 weeks for each sector.
Trend Adjusted Equal Weight of 5 Strong Sectors	At the end of the last week of each month, attribute an equal weight (i.e. 20%) to each sector falling in the 5 best ranks
	Multiply each sector weight by the global exposure calculated in Strategy 1. For example, if a 20% is attributed to each sector (100% ÷5 = 20%) and the global exposure is 60%, then a 12% will be allocated to each sector (12% x 5 = 60%)
Strategy 3 **Trend Filtered Strong Sectors**	At the end of each month, each of the best trending sectors calculated as in Strategy 2 is selected, but only if the longer term rate of change (26 weeks) is positive. If negative, its reserved stake will be maintained in cash. If, for example, only 3 out of the five relatively stronger sectors show a positive rate of change at 26 weeks, then a 60% exposure is attributed to this strategy (5 sectors x 20% = 100%, only 3 in uptrend x 20% = 60%).

Figure 2. Rate of Change, 26 Weeks on 10 Sector Indexes in 2016

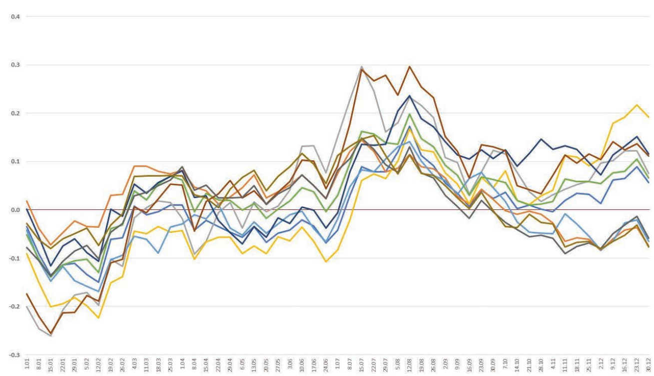


Figure 3. Percentage of Sectors With Positive Rate of Change, 26 Weeks (histograms) and MSCI® World 2015–2016 (line)

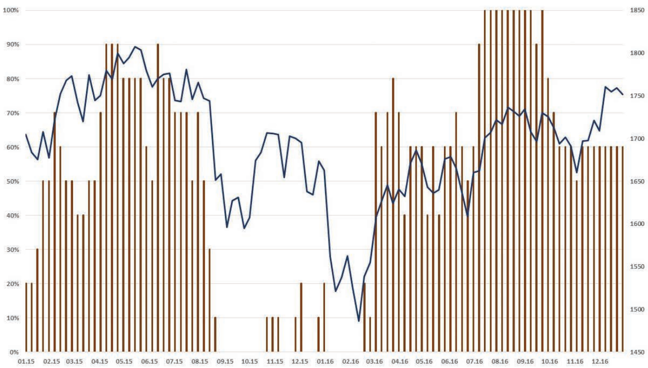


Figure 4. Simulated Equity Curve for Strategy 1 (green line) Compared With MSCI® World (blue line) and Equal Sectors Weighting (red line)

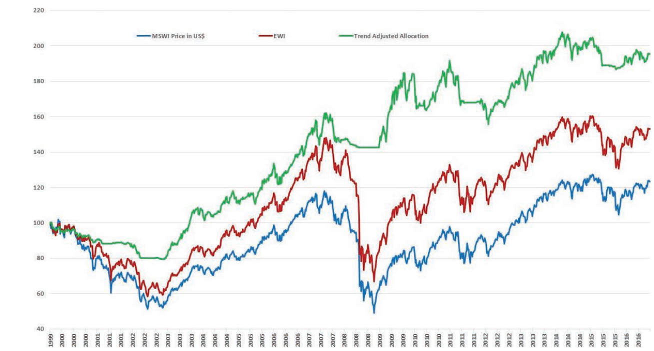
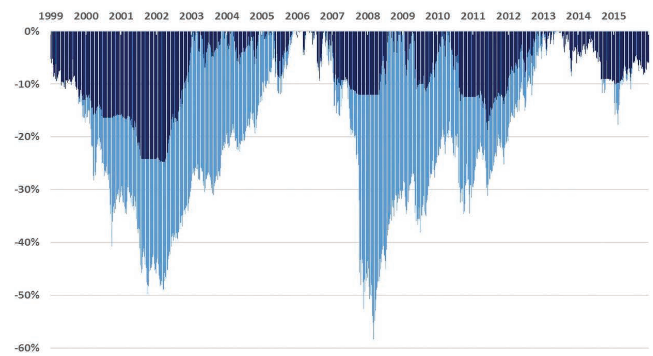


Figure 5. Equity Drawdowns for Strategy 1 (dark blue) Compared With MSCI® World (light blue)



Results

All the results analyzed are obtained from simulations made on weekly data of MSWI global sector indexes in U.S. dollars between 2000 and 2016. A comparison is made with the simulated result on the global ETFs (see Table 1); historical data only date back to September 2006. All the relevant figures, including the maximum drawdowns, are calculated on weekly closes.

Strategy 1: Trend Adjusted Equal Weight of 10 Sectors

The dynamic allocation of 10 equally weighted sectors (see the summary in Table 2) considers a variable exposure between 0% and 100%. If the percentage of sectors showing a positive momentum at long term is smaller than 100%, then the invested percentage of each single sector is scaled down accordingly. The results of the simulation are shown in Table 3.

Table 3. Simulation Results Trend Adjusted Equal Weight Strategy

Trend Adjusted Equal Weight of 10 Sectors			tested on:	
04.2007-12.2016 - 9.75 yrs	MSWI	EWI	Indexes	ETFs
Cumulated Return	1.5%	8%	37%	30%
Annualized (CROR)	1.5%	1.9%	3.3%	3.7%
Standard Dev. Annualized	19%	19%	9%	10%
Deviation/CROR	12.7	10.2	2.8	2.6
Maximum Drawdown	-58%	-55%	-19%	-19%
2000-2016 - 17 years	MSWI	EWI	Indexes	
Cumulated Return	23%	53%	95%	
Annualized (CROR)	1.2%	2.5%	4.0%	
Standard Dev. Annualized	17%	17%	9%	
Deviation/CROR	14.0	6.5	2.2	
Maximum Drawdown	-58%	-55%	-21%	

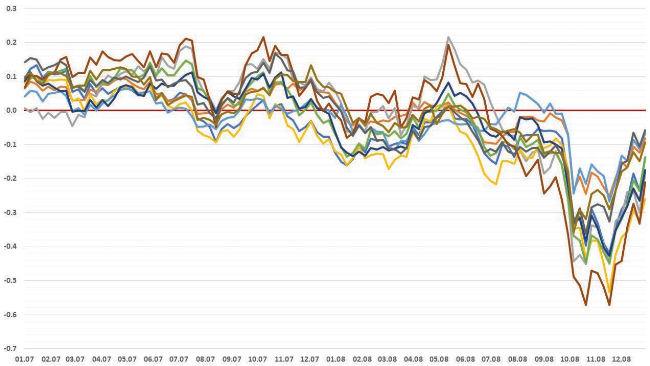
Strategy 2: Trend Adjusted Equal Weight of Five Strong Sectors

The sectors are ranked by the respective values of an average of three rates of change with different speeds (see the summary in Table 2). The five strongest are selected each month for an equal allocation, but the exposure is then calibrated by the weighting factor employed in Strategy 1.

Table 4. Simulation Results Trend Adjusted Equal Weight Five Strong Sectors

Trend Adjusted Equal Weight in 5 Strong Sectors			tested on:	
04.2007-12.2016 - 9.75 yrs	MSWI	EWI	Indexes	ETFs
Cumulated Return	1.5%	20%	82%	83%
Annualized (CROR)	1.5%	1.9%	6.4%	6.4%
Standard Dev. Annualized	19%	19%	10%	11%
Deviation/CROR	12.6	10.1	1.6	1.7
Maximum Drawdown	-58%	-55%	-17%	-17%
2000-2016 - 17 years	MSWI	EWI	Indexes	
Cumulated Return	23%	53%	191%	
Annualized (CROR)	1.2%	2.5%	6.5%	
Standard Dev. Annualized	17%	17%	10%	
Deviation/CROR	14.0	6.5	1.5	
Maximum Drawdown	-58%	-55%	-17%	

Figure 6. Composite Momentum on 10 Sectors 2007–2008



Strategy 3: Trend Filtered Strong Sectors

Five stronger sectors are selected at the end of each month, as with Strategy 2, but those with a negative rate of change at six months are discarded. In this case, the exposure is not calibrated by the weighting factor like in the Strategies 1 and 2. Yet, the dynamic total exposure is given by the number of sectors in which the trend indicator is positive. (The total exposure can range between 0% and 100% by steps of 20%. See Strategy 3 in Table 2).

Table 5. Simulation Results Trend Filtered Allocation Five Strong Sectors

Trend Filtered Strong Sectors			tested on:	
04.2007-12.2016 - 9.75 yrs	MSWI	EWI	Indexes	ETFs
Cumulated Return	1.5%	20%	93%	61%
Annualized (CROR)	1.5%	1.9%	7.0%	6.6%
Standard Dev. Annualized	19%	19%	12%	13%
Deviation/CROR	12.6	10.1	1.7	2.0
Maximum Drawdown	-58%	-55%	-22%	-22%
2000-2016 - 17 years	MSWI	EWI	Indexes	
Cumulated Return	23%	53%	226%	
Annualized (CROR)	1.2%	2.5%	7.2%	
Standard Dev. Annualized	17%	17%	12%	
Deviation/CROR	14.0	6.5	1.6	
Maximum Drawdown	-58%	-55%	-23%	

Figure 7. Simulated Equity Curve for Strategy 3 With (blue line) and Without Trend Filtering (green line)

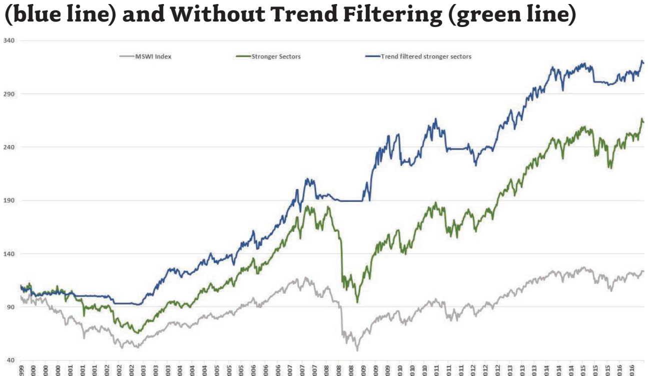


Table 6. Monthly Sectors Allocation for Strategy 3, 2014–2016

	Consumer Disc.	Consumer Staples	Energy	Finan-cials	Health Care	Indu-strials	Techno-logy	Mate-rials	Tele-com	Utilities	
Jan-14	20%		20%	20%	20%			20%			100%
Feb-14		20%	20%	20%	20%			20%			100%
Mar-14			20%	20%	20%			20%	20%		100%
Apr-14			20%	20%	20%	20%			20%		100%
May-14			20%		20%	20%	20%		20%		100%
Jun-14				20%	20%	20%	20%		20%		100%
Jul-14				20%	20%	20%	20%		20%		100%
Aug-14		20%		20%	20%	20%			20%		100%
Sep-14	20%			20%	20%	20%			20%		100%
Oct-14	20%			20%	20%		20%	20%			100%
Nov-14	20%			20%	20%		20%		20%		100%
Dec-14				20%	20%		20%	20%	20%		100%
Jan-15				20%	20%		20%	20%	20%		100%
Feb-15				20%	20%		20%	20%	20%		100%
Mar-15			20%	20%	20%		20%	20%			100%
Apr-15			20%	20%	20%		20%	20%			100%
May-15	20%			20%	20%			20%		20%	100%
Jun-15	20%	20%		20%	20%			20%			100%
Jul-15	20%			20%	20%			20%		20%	100%
Aug-15	20%			20%	20%		20%	20%			100%
Sep-15											0%
Oct-15											0%
Nov-15							20%	20%			40%
Dec-15				20%			20%	20%			60%
Jan-16				20%			20%				40%
Feb-16											0%
Mar-16				20%			20%		20%		60%
Apr-16		20%	20%	20%					20%	20%	100%
May-16		20%	20%			20%			20%	20%	100%
Jun-16		20%				20%	20%		20%		80%
Jul-16		20%				20%	20%		20%	20%	100%
Aug-16		20%	20%	20%	20%				20%		100%
Sep-16	20%	20%	20%	20%		20%					100%
Oct-16	20%	20%	20%	20%		20%					100%
Nov-16	20%	20%	20%	20%		20%					100%
Dec-16	20%	20%	20%	20%		20%					100%

Figure 8 shows the correlation at three months between the World Index and the result simulated for Strategy 3. The correlation coefficient has been calculated on 12 weeks of data between the weekly returns of the MSWI and the equity curve of a portfolio invested, between 2000 and 2016, by following the Strategy 3 (five strong sectors monthly selection, filtered by positive trends).

Figure 8. Correlation at 3 Months Between the Equity Curve of Strategy 3 and MSCI® World

The relative strength resulting from the ratio between the equity curve of Strategy 3 and the World index is shown in Figure 9, together with a linear regression line.

Figure 9. Relative Strength Equity Curve Strategy 3 vs. MSCI® World With Linear Regression in Red

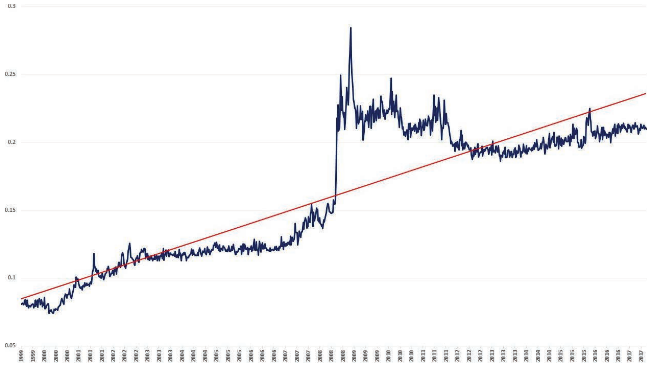


Table 7. Three Simulations Compared

2000-2016 - 17 years	MSWI	EWI	Method 1	Method 2	Method 3
Cumulated Return	23%	53%	95%	191%	226%
Annualized (CROR)	1.2%	2.5%	4.0%	6.5%	7.2%
Standard Dev. Annualized	17%	17%	9%	10%	12%
Deviation/CROR	14.0	6.5	2.2	1.5	1.6
Maximum Drawdown	-58%	-55%	-21%	-17%	-23%

Different Parameters Tested

All the results of the simulations have been calculated on a set of rates of change at 8, 13 and 26 weeks. The number of selected sectors in the relative strength strategies is five.

Other parameters have been tested, too. A range between 20 and 30 has been chosen for the long-term rate of change. A number of sectors ranging from one to 10 has been tested for the relative strength strategies. Figures 10 and 11 show the key figures resulting from different parameters tested on Strategy 2.

Figure 10. Simulations on Strategy 2 With Different Speeds for Long-Term RoC

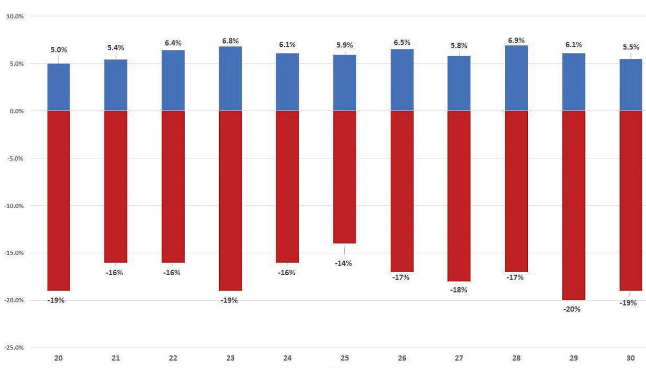
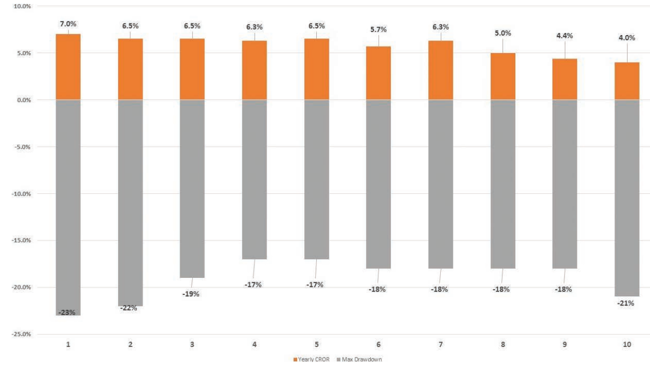


Figure 11. Simulations on Strategy 2 With Different Numbers of Sectors



Discussion

The comparison between the MSCI® World index and the equal weighting of the sectors to which its components belong is an interesting starting point. In fact, there are big disparities in the sector weighting of the World index, as just three sectors comprise 50%. The reason is capitalization: the market value of a stock increases with its quote, so the stronger groups tend to increase their weight over time. This is true for every market-value weighted index. The equal weighted benchmark that has been calculated in this study, made by simulating a constant equal rebalance of the 10 most important sector indexes, differs from a classic equally weighted version because it does not depend on the number of stocks that can be much larger for a sector than another. The results between the MSCI® World and the equal weighting of sectors diverge in terms of return (see Figure 1), and this is just due to the difference in strengths among groups of stocks, while the volatility figures, like standard deviation and drawdowns, are quite similar. In this study, the results of the simulated strategies have been also compared to an equal sector weighting for a more objective evaluation of their effectiveness.

Measuring the trend by evaluating the momentum of the sectors that compose the market corresponds to a bottom-up approach. This methodology leads to the construction of a breadth-indicator that measures the participation of the sectors to the market trend. It is easy to normalize, as the number of trending sectors is expressed as a percentage of the total, and its value varies with the direction of the market. Figure 3 is a good example: in 2015 and 2016, the world equity markets experienced a severe downtrend in the second half of 2015 and then reversed their direction on the upside. The percentage of sectors showing a positive momentum at six months decreased gradually when the trend reversed to the downside and went back to zero in the fourth quarter. This indicator helps to determine the level of exposure in the market and allows the buildup of a dynamic allocation. This is the principle that has been adopted for Strategy 1 (see Table 2), which considers an equal distribution among 10 sectors but calibrates the global exposure to the percentage that has been obtained from the breadth indicator described. The simulated results of this strategy, as shown in Table 3, show that the gradual downsizing of the investment exposure with the strength of the global trend can reduce the volatility dramatically. The annualized standard deviation, with a historical value close to 20% for the benchmarks (on weekly data), decreases to 9%, so the maximum drawdowns are reduced by more than half. The advantage of skipping the bear markets results, of course, in a better return over the long run, especially if the period under exam is strewn with negative cyclical phases like the first decade of the century. A comparison between the drawdowns of the market and those produced by the trend-adjusted strategy is shown in Figure 5. Furthermore, avoiding the sharp falls produced by the bear markets may allow for the recovery of the intermediate losses much more quickly: consider that it took seven years for the World index (expressed in U.S. dollars, without reinvestment of dividends) to get back to the highs of 2007, while a dynamic trend-following strategy could have recovered in 2009.

The employment of a methodology based on momentum is especially interesting when examining relative trends. Much has been written about sector rotation and the advantage of improving the quality of the investments returns by choosing the strongest sectors and discarding the others. A method for measuring relative trend is given by the comparison among the values of the rates of change given by each single sector index, as shown in Figure 2, where the values of a rate of change at six months of 10 sectors in 2016 have been superimposed. Even if a global common bias in direction is visible, the differences in strength are evident. For example, 4 out of 10 sectors showed negative momentum values at the end of 2016. No matter which ones they were, what is important is defining a technique able to detect the sectors on the top of the wave that are poised to perform better, and to discard them once they fall to the lower levels.

This concept has been applied to both Strategy 2 and Strategy 3, described as Trend Adjusted Equal Weight of 5 Strong Sectors and Trend Filtered Strong Sectors. The strength of the sectors is determined by an average of rates of change with three different speeds—8, 13 and 26 weeks—representing three significant time spans at 2, 3 and 6 months, respectively.

Strategy 2 considers a monthly rotation in the sectors with stronger momentum that are equally weighted at the end of each month, and then the global exposure is calibrated according to the percentage determined in Strategy 1, the breadth indicator described above. Strategy 3 adopts the same selection criteria for the sectors but discards those that do not fill the trend requirement. The highest values for momentum are chosen for the selection, but only the positive values are considered. If negative, the stake dedicated to that specific sector will be maintained in cash. This is another way of defining a dynamic exposure: in a bear market even the strongest sectors, less weak in this case, could be in downtrend, so they will be avoided and the strategy will stay in cash.

Two important considerations emerge when evaluating the results of the simulations applied to these two methods. First, we can reasonably enhance our expectations by constantly selecting the sectors that are better classified in terms of momentum. The difference between the results of Strategy 2 versus Strategy 1 is quite clear: in Table 6, where the three strategies are compared, we can see that much better return is obtainable from Strategy 2 for the same amount of risk, and the ratio between the annual standard deviation and the yearly compounded rate of return for capital can be cut down below 2. Yet, just adopting a relative momentum strategy, without employing a filter for downtrends, can improve the investment return at medium-long term but does not reduce risk, if not marginally. An example is given by the chart in Figure 7, where the equity line for the strategy simulated without filtering out the negative trends in sectors, although much more rewarding than a passive investment, presents the same risk of drawdown.

Further consideration deserves the analysis of correlation among the strategies and the benchmark. It is quite evident that an efficient strategy requires a strong correlation with the market during an uptrend; in this case, the coefficient should get closer to 1. If the strategy is good enough to avoid or reduce the market exposure significantly in the worst periods, then its correlation with the market should get away from the high range in negative cycles. This is what happens with a calibrated trend strategy: an example is given in Figure 8, where the correlation coefficient has been calculated between the weekly returns at three months of the MSCI® and the equity line of Strategy 3. Most of the values for the coefficient have been standing within the range 0.80–1.00 in bull markets and fell to near zero after that negative trend occurred.

How strong are these methods when compared with a passive investment? A relative strength, a ratio between the two equity curves, Strategy 3 and MSCI®, is shown in Figure 9. As we can see, the strategy is generally stronger than the market, except in some period between 2009 and 2012. Although the regression line of the relative trend, drawn by the red line in the chart of Figure 9, is positively inclined over 17 years, this period of relative weakness in the strategy can be explained by the late reaction of the momentum indicators to the sharp reversals. On one hand, a disciplined trend following could prevent the investor from being devastated by the bear market, but on the other hand, the reactions to the recovery were late. This is quite normal when the volatility skyrockets and the market reactions are unmanageable.

There are some considerations regarding the parameters chosen. All the simulations are based on values of 8, 13 and 26 weeks for momentum, and five sectors have been chosen for the relative filtering. Such values are not over-optimized. Figure 10 shows the results that have been obtained by simulating different speeds for the long-term momentum, which is more relevant, in the range 20 to 30 by steps of 1. The results are quite consistent, in terms of both returns and drawdown, so we can affirm that the effectiveness of the 26 weeks is not random.

Figure 11 shows the differences in the results of Strategy 2 when different numbers of sectors are chosen. It is interesting to note how the potential return is inversely proportional to the number of sectors included in the strategy. This is due to the fact that a more targeted choice contains more potential but also more risk. A number of sectors in the middle of the available range looks the most appropriate for an optimal reward/risk ratio.

Finally, the simulations have been made without considering transaction costs. The low frequency of transactions required to maintain the strategies (no more than one per month for each sector, only in case of a change of conditions) allows the dividend yields to be considered an adequate source of revenues. They are not included in the price series analyzed, and the ETFs used in this study provide an average of about 2% dividend yield, depending on the single sectors.

Conclusion

Trend following, a basic tenet of technical analysis, can contribute to the quantitative portfolio strategies in a valuable way. The quality of the returns of a diversified investment strategy in equity sectors can be improved by analyzing single sector trends through a method based on multiple rates of change.

Sector rotation enhances the returns of a portfolio, but to effectively reduce the risk of drawdowns, we need a method that is capable of filtering out the downtrends in absolute and not only relative terms.

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Empirical Mode Decomposition

Application to Financial Time Series With Chart Projection

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Abstract

In this paper, the Empirical Mode Decomposition (EMD) is adapted to financial time series, and applications in the area of technical analysis are provided. The EMD provides a data-driven decomposition into several, non-stationary waves and a trend component. Hence, it can be seen as a tool to extend the classical cycle-theory in technical analysis, which is based on waves with constant wavelengths. Two refinements are introduced to the core algorithm of the EMD. First, the stability of the EMD is enhanced at the edge by introducing additional supporting points at the boundary in the sifting process, a subroutine of the EMD. Secondly, the stability of the decomposition with regard to new available data as time goes by is enhanced by introducing a distinct condition to stop the sifting process. One important application of the EMD presented in this paper is the price projection. Since the price can be decomposed into several waves and a trend component by the EMD, a forecast can be obtained by extrapolating the waves using the mathematics of oscillations. As a further application of the EMD, a new type of moving average is also introduced. Finally, the price projection method and simple EMD-related trading strategies are exemplarily discussed on the S&P 500 index.

Introduction

Especially at the turn of the year, annual outlooks for the financial markets are quite popular. These are often based on typical cycles with a fixed period (e.g., the one-year cycle to cover seasonality or the four-year U.S. presidential cycle). Hence, they are based on cycles with a constant period length—that is the basic assumption in classical cycle theory. On the other hand, experience told us that economic cycles differ as well in their duration as in their magnitude. Hence, it would be great to have a technique to project a chart, based on cycles with changing amplitude or wavelength.

To analyze such non-steady waves in general, (Huang and others 1998) presented the Empirical Mode Decomposition, or abbreviated EMD. A first adaption of this algorithm to financial time series has been performed by (Dürschner 2014). Further specifications in the application of the EMD to market data will be presented in this paper. As a result, one obtains a decomposition of a time series into several smooth waves (Intrinsic Mode Functions, IMF) and a basis trend. Since the single waves and the trend component could easily be predicted, one could obtain a base scenario for the future price behavior based on the assumption that the underlying waves will continue their course with their current characteristics. This idea has been published in (Reiss 2017).

Empirical Mode Decomposition

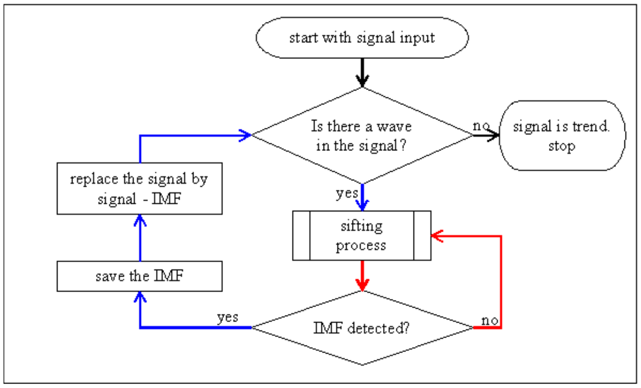
The basic algorithm

Typically, the technical analyst starts the analysis from the large timescale and refines the analysis by breaking down the timeframe. The EMD works just the other way around: The smallest wave is extracted at first, and the next iteration identifies the smallest remaining wave, and so on until all waves have been segregated. The core algorithm is shown in the flow chart (Figure 1). As long as the signal (e.g., given by the price series of an equity or index) includes a wave, a so-called sifting process is applied until an IMF has been isolated. The determined IMF is stored and subtracted from the input signal, and this decomposition will be repeated until the remaining signal is not wavy anymore. Finally, the remaining signal gives the trend component, and the complete decomposition consists of this trend component and all identified IMFs.

Hence, there are two nested loops in the algorithm: The outer loop (printed in blue) will be iterated until the signal is not wavy anymore. To concretize this condition, the outer iteration will be performed as long as the signal has at least one local minima and at least one local maxima. To be precise, a local maxima (minima) is a data point that is larger (smaller) than its left and right neighbor. Since the boundary points of the signal only have one neighbor, they are never a local maximum or local minimum by this definition.

By construction, it is clear that the sum of all IMFs and the trend component yield to the original input, since in each iteration of the outer loop, the identified IMF is subtracted from the input signal and the result is the input for the next iteration. Hence, the following relation holds, where N denotes the number of identified Intrinsic Mode Functions:

Figure 1. Flow Chart of the EMD Algorithm



$$\text{Signal}(t) = \text{Trend}(t) + \sum_{i=1}^{N} \text{IMF}_i(t)$$

The inner loop of the algorithm, which is shown in red in the flow chart, is used to identify the next and smallest available wave from the data. This wave will be the next IMF and is segregated by multiple applications of the sifting process. A clear stopping criteria for this loop is required too. From (Huang and others 1998), there is one clear criteria for an IMF: The number of extrema (minima or maxima) and the number of zero crossings must be either equal or differ at most by one. On the other hand, the stopping condition is not that precise since the sifting process should be iterated several times but not be too excessive. For the application on financial time series in this paper, the original IMF condition is reformulated, and the sifting iteration is stopped if the sifting process has been performed at least five times, and all local maxima of the IMF are positive and all local minima of the IMF are negative.

The sifting process

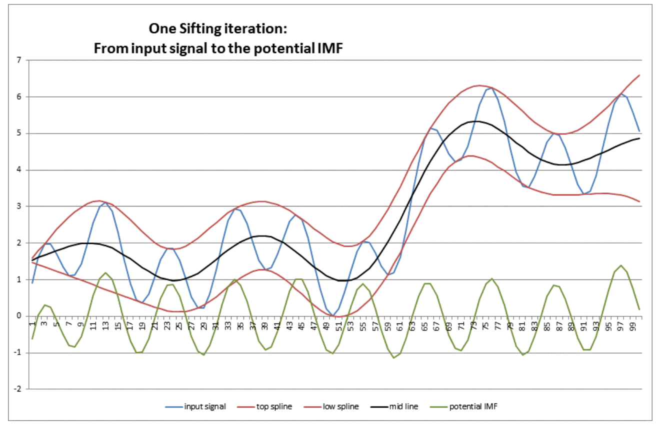
The essential part of the EMD algorithm is the sifting process, which is used to identify the wave with the shortest wavelength from the signal. To explain the sifting process by using terms from technical analysis, at first some bands are determined to capture the input signal. Then, an average is defined by the arithmetic mean of the upper and lower band. The difference between the input signal and the average results in an oscillator, which is the result of the sifting process.

The mathematical and precise definition of the sifting process as defined in (Huang and others 1998) is given by the following steps:

1) **Identify the upper band.** At first, all local maxima of the signal are determined. The upper band is defined as the cubic spline with natural boundary conditions supported by the local maxima. For the definition and an algorithm to compute a cubic spline, see (Press and others 1992).
2) **Identify the lower band.** According to the upper band, the lower band is computed as the cubic spline with natural boundary conditions supported by all local minima of the signal.
3) **Calculate the midline.** The midline is computed as the arithmetic mean of the previously identified upper and lower band.
4) **Determine the potential IMF.** The potential IMF is obtained as the difference of the input signal and the midline. If the result is not an IMF or the sifting process has not been iterated at least five times, this potential IMF serves as input signal for the next sifting process.

To clarify the sifting process, the first iteration of the sifting process is shown in Figure 2, inspired by the example of (Kim and Oh 2009). From the input signal (blue line) the local maxima are identified and a spine is computed, which is supported on the maxima (red line). Analogous, the lower spline (red line) is computed as the spline supported by the local minima of the signal. The average of the both splines (both in red) is the midline (black line). The difference between the input signal (blue line) and the midline (black line) is the result of the sifting, the potential IMF (green line).

Figure 2. Explaining One Iteration of the Sifting Process



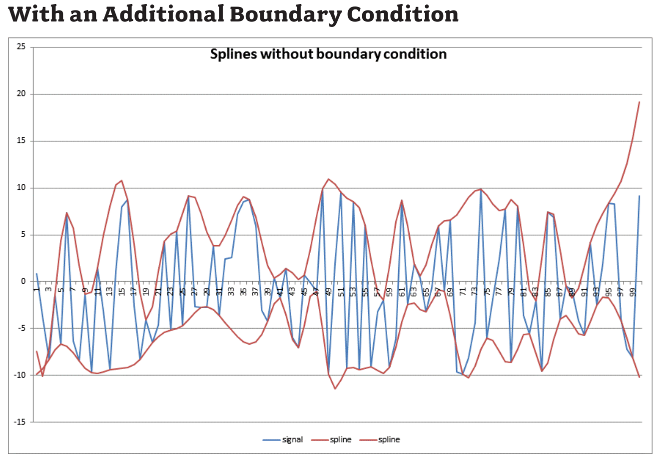
Stabilization at the boundary

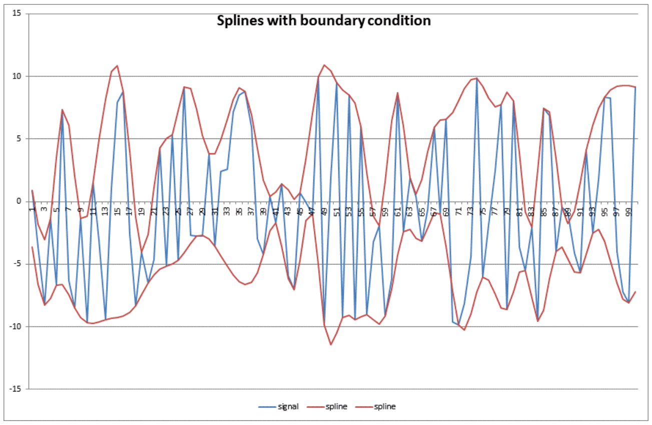
The computation of the upper and lower band based on a cubic spline faces a problem, which was already noticed in the original paper on the EMD. At the left and right boundary, the spline will either strongly increase or strongly decrease, since the cubic spline is dominated by its cubic term. As a consequence, the IMF also will be strongly increasing or decreasing, but they lose their oscillatory behavior. In the left picture of Figure 3, one can obtain the behavior of the splines without boundary condition. At the left boundary, the top band is decreasing so fast that the bands even cross at the right boundary; however, the spines depart from the usual signal area. Both behaviors are disappointing for a typical band.

To obtain a smooth oscillation by the sifting process at the boundaries, a reasonable extension of the upper and lower band must be provided. As an additional boundary condition for the spline, at the left and right boundary, additional supporting points for the spline are introduced. The value of these supporting points are the following:

- For the upper band: The maximum of the signal at the boundary and the value of the nearest local maximum.
- For the lower band: The minimum of the signal at the boundary and the value of the nearest local minimum.

Figure 3. The Difference of a Band of Splines Without or With an Additional Boundary Condition





Using this additional boundary condition on the upper and lower band, the splines behave as expected, which can be seen in the right picture of Figure 3. The splines neither cross each other nor are they moving away from the signal area.

This kind of stabilization of the band at the boundaries in the sifting algorithm is applied throughout this paper. Keeping this in mind, also the condition of the outer loop of the EMD algorithm comes clear: Since the cubic splines requires at least three supporting points and by this stabilization technique there are two supporting points given at the boundary, at least one local maximum and at least one local minimum is needed to perform the sifting algorithm. Since the local extremum is never at the boundary by definition, there are at least three different supporting points given for each spline.

Reviewing some modifications of the sifting process

In the original EMD algorithm, the sifting process is based on a cubic spline to compute the upper and lower band. One the one hand, this yields to the instability at the boundaries as explained above, on the other hand, the spline is—at least by theory—influenced by all local maxima (minima), and hence, data points far away also impact the value of the spline. These drawbacks yield to the idea of using other techniques to compute the upper and lower band in the sifting process. Possible alternatives are:

- Linear Interpolation
- Sub-spline
- Akima-spline

The sub-spline as the Akima-spline is an interpolation based on a polynomial of third degree. This polynomial is computed for each segment between two neighbored maxima (minima). For each of these polynomials, four conditions are given to match the coefficients: The value and the first derivative at the left and right end of the segment. The difference between the Akima-spline and the sub-spline is related to the estimation of the first derivative at the boundaries of each segment.

To illustrate the general impact of the four methods to compute the upper and lower band in the sifting algorithm, the EMD for the S&P500 in the period of 2008–2017 is performed. Since a continuous and strictly monotonic transformation should not impact the oscillations in the signal, the EMD is applied on the prices and on the log of the prices. The results are summarized in Table 1.

As a result, the cubic spline yields the smoothest IMFs, the decomposition yields the same number of waves if applied on the prices or the log-prices, and the number of IMFs needed to decompose the data is minimal. Hence, the cubic-spline, as suggested by the originators of the EMD, is the best way to compute the band in the sifting process.

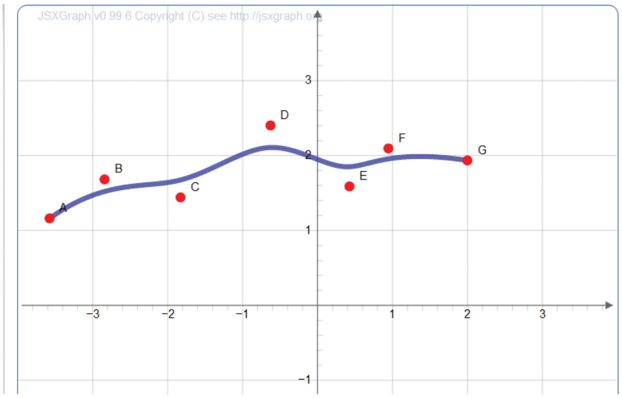
Table 1. Comparison of Several Sifting Process Variations

Band algorithm	Number of Waves		Style of the IMFs (waves)
	Price	Log (Price)	
Linear	8	9	The IMFs are rather ragged
Akima-spline	9	9	IMFs are smooth, the IMF9 is almost a trend and quite big in contrast to IMF8 and IMF7
Sub-Spline	8	9	Quite smooth for the log-prices, but sometimes ragged on the original price
Cubic-spline	7	7	Smooth IMFs and similar decomposition for original and log prices.

Also the B-spline is studied in the literature. (Dürschner 2014) proposed to use the B-spline to compute the upper and lower bound. But the B-spline does not bound the signal, but rather interpolates between the maxima (minima), and the upper (lower) band is not an envelope of the signal anymore, as illustrated in Figure 4. Since the most extreme values in the market data are related to maximum emotional experience of the market participants, they are too relevant to leave them outside the bands.

Since the B-spline is rather used to interpolate between points than to construct a curve through some points, (Riemenschneider and others 2014) provided another idea. Instead of defining an upper and lower band and defining the midline as the mean of the two bands, they suggested using all extrema, hence minima and maxima, and the B-spline defined by these points is the midline of the sifting process. Their idea allows a more rigorous theoretical study of the algorithm, but their analysis also showed that the application of the B-spline EMD "gives very comparable results to those of the original envelope approach" (Riemenschneider and others 2014, p. 45).

Figure 4. Example of a B-Spline. The B-Spline Does Not Touch the Supplied Data Points.



(Obtained from http://jsxgraph.uni-bayreuth.de/wiki/index.php/B-splines)

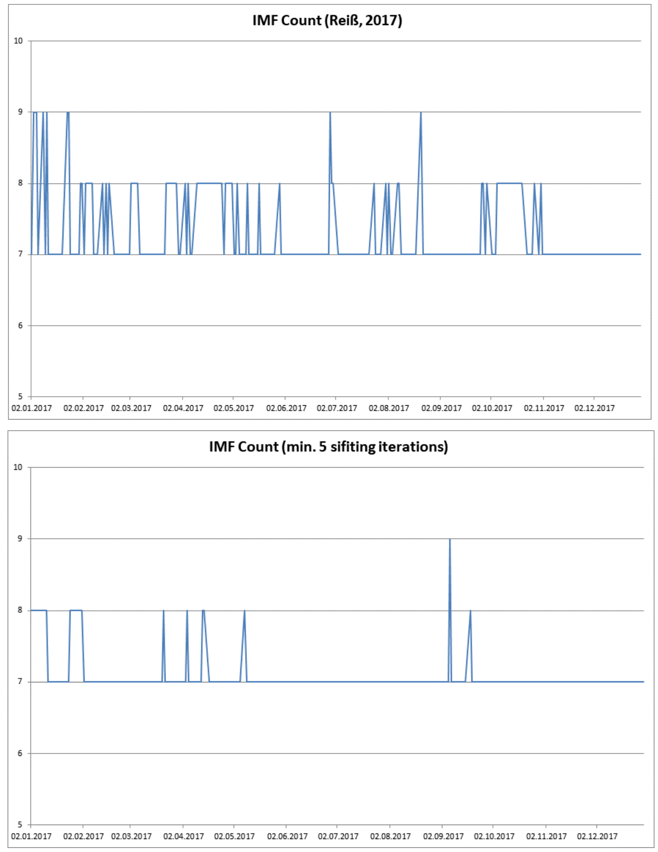
A note on time shift stability of the EMD

To use the EMD in trading systems, one also needs a stability of the decomposition with regard to the time elapsing. For example, if the EMD is applied on a fixed horizon of 10 years, on the next trading day there is a new data point on the right hand of the signal, and on the left hand side, one data point disappears. But of course, the decomposition of the data should remain stable as time goes by.

It turned out that this stability is linked to the condition of when to stop the sifting process. Beside the condition—that the maxima of an IMF must be positive and the minima of an IMF must be negative—additional criteria are needed to ensure that the result is smooth enough. For applications of the EMD on financial time series, (Dürschner 2014) suggested a criteria based on orthogonality of the IMF, and (Reiss 2017) proposed a criteria, that the IMF fulfills the maxima-minima-condition under several iterations of the sifting process. In both approaches, the stability under time elapsing has not been studied.

In comparison to (Reiss 2017), the approach in this paper—to iterate the sifting process at least five times—is more stable as time goes by. To verify this statement, the empirical mode decomposition is performed for each trading day of the year 2017 on the S&P500—based on a 10-year time horizon. At each day, the number of IMFs are presented in Figure 5, where the sifting termination condition of this paper and of (Reiss 2017) is shown.

Figure 5. Comparison of the Number of IMFs Related to Different Sifting Break Conditions



Obviously, the algorithm of this paper is much more stable. This can also be seen from the statistics of the results: The number of days on which 7, 8, or 9 IMFs have been detected are given in Table 2, as well as the variance of this data and the number of stable days. To define a "stable day," a certain date is called stable if the same number of IMFs have been detected by the majority over the last 10 trading days.

The definition of stable days and the handling of unstable days are relevant for developing a trading system based on the EMD, since one could only achieve a reliable system if one refers at each day on a similar decomposition compared to the day before.

Table 2. Statistics of the Two Different Sifting Break Conditions in 2017 on the S&P 500

		IMF Count (Reiß, 2017)	IMF Count (min. 5 sifiting iterations)
Number of IMF			
	7	190	239
	8	61	20
	9	9	1
Variance		**0,28**	**0,09**
Number of stable days		**190**	**233**

Introduction of the EMD Moving Average (EMDMA)

Definition of the EMDMA

One application of the classical cycle theory is the construction of adapted moving averages. Let *M* be the wavelength of a dominant cycle measured in days; one should use a simple moving average of *M* days to uncurl this cycle. Following (Dürschner 2014), one could also obtain adapted moving averages based on the EMD, which is aligned to the identified waves. By construction, the EMD decomposes the price time series *X(t)* into *N* Intrinsic Mode Functions and one Trend component, which fits to the summation principle in cycle theory:

$$X(t) = \mathrm{Trend}(t) + \sum_{i=1}^{N} \mathrm{IMF}_i\,(t)$$

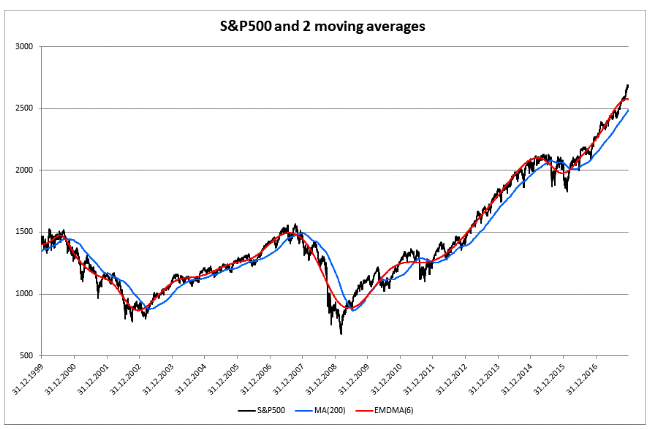
The proportionality principle also holds: The wavelength and amplitude of IMF_i (t) increase generally with the order *i*. Hence, an EMD based moving average of order *n* can be defined by

$$\mathrm{EMDMA}(n, t) := \mathrm{Trend}(t) + \sum_{i=n}^{N} \mathrm{IMF}_i\,(t)$$

Properties of the EMDMA

To understand the EMDMA in comparison to the standard moving average (MA), the S&P 500 from 2000–2017 is shown together with the MA(200) and the EMDMA(6) in Figure 6. The parameter of the EMDMA is chosen such that the EMDMA swings in a similar fashion as the MA(200). One observes two important differences of these two moving averages:

Figure 6. A long term chart to illustrate the different behavior of MA and EMDMA



1) In periods of a strong trend, the price is located above the MA. With respect to the EMDMA, the price crosses the EMDMA quite frequently—even in trending phases (e.g., 2012–2014 or 2016–2017).
2) After a correction, the EMDMA turns faster from being falling to rising than the MA (e.g., 2002, 2009, 2015).

The second point inspired (Dürschner 2014) for a simple interpretation of the EMDMA: A rising EMDMA is a long signal, and a falling EMDMA is a short signal. Later in this paper a back test of a trading system based on this simple idea is shown.

The EMD Based Price Projection

The key idea of the price projection

A key idea of this paper is to compute a price projection based on the EMD. By construction of the EMD algorithm, the following relationship holds as mentioned before:

$$\mathrm{Price}(t) = \mathrm{Trend}(t) + \sum_{i=1}^{N} \mathrm{IMF}_i(t)$$

The advantage of this equation is that the components on the right side of the equation could be forecasted due to the fact that the IMFs are wavy and hence follow the laws of oscillation, and that the trend component, which does not contain any oscillation by definition, could be extrapolated linearly.

The time horizon of the price projection will be one year, and one has to differentiate between shortwave and longwave IMFs. For shortwave IMFs, one has to consider a change in the amplitude or frequency of the wave since the EMD gives a decomposition in non-steady waves. To cover this variation, the forecast of such waves based on a harmonic oscillation with damping or stimulation seems to be quite realistic. The idea of the damping or stimulation is to restore the current oscillation to its average energy state.

For longwave intrinsic mode functions, however, an approximation by a pure harmonic oscillation could be considered, since these will change their amplitude or frequency at a slow rate only. Hence, such treatment can only be considered if the wavelength is clearly larger than the forecast horizon, which is assumed to be one year. Within this paper, an IMF is called a longwave IMF if its wavelength is larger than two years, and all IMFs with a shorter wavelength are called shortwave.

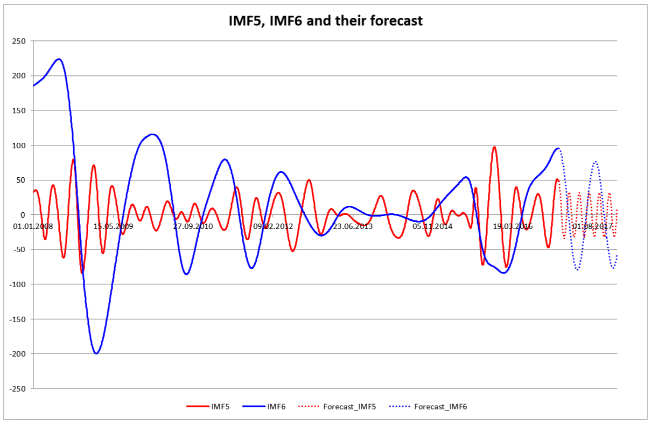
The concrete techniques for the forecasts of the EMD components are presented below. The EMD-based projection is then simply given by

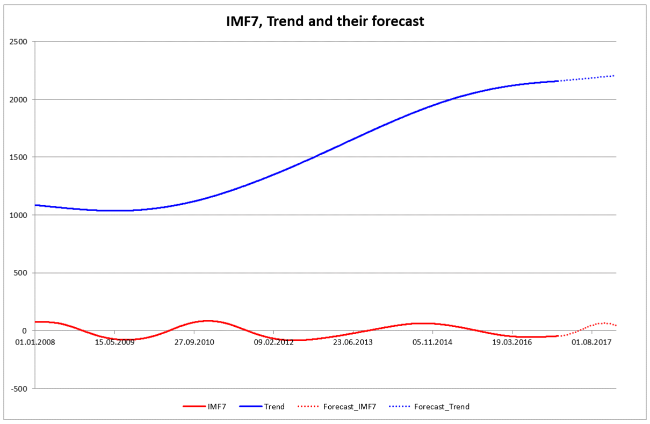
$$\mathit{Forecast}[\mathrm{Price}(t)] = \mathit{Forecast}[\mathrm{Trend}(t)] + \sum_{i=1}^{N} \mathit{Forecast}[\mathrm{IMF}_i(t)]$$

To also cover sufficient information from long waves, the period of the decomposition should not be to short; for the analysis in this paper, the time series covers 10 years.

To illustrate the forecast of the waves, Figure 7 shows the typical continuation of the EMD components. The waves are extrapolated by the algorithms described below. One can see that the extrapolation of the smaller IMF 5 yields to a harmonic oscillation, the IMF 6 is correcting rather fast since its current elongation is bigger than the average amplitude. The continuation of IMF 7 and the trend component fits to usual expectation.

Figure 7. Some Components of the EMD (Solid) and Their Continuation (Dotted)





As a side note, one can modify this technique if the price varies in the order of a magnitude or even more, which is more likely to be the case if the time series covers an even longer period or a more volatile market. In such a situation, the price projection could be performed on a logarithmic scale as pointed out in (Reiss 2017). In this case, the EMD is performed on the log (price), and the projections on the IMFs and the trend are done on the same way as described below. Hence the price projection is then given by:

$$Forecast[\text{Price}(t)] = \text{Exp}\left(Forecast[\text{Trend}(t)] + \sum_{i=1}^{N} Forecast[\text{IMF}_i(t)]\right)$$

Forecasting a shortwave IMF

Excursus: The physics of oscillations

The basic properties of harmonic oscillations can be found in standard physics textbooks (e.g., (Gerthsen and Vogel 1993). The harmonic oscillation can be represented by

$$X(t) = A \sin(\omega\, t)$$

where A is the amplitude and ω is the angular frequency of the oscillation. Its wavelength is given by $\lambda = \frac{2\,\pi}{\omega}$. The first and the second derivative of $X(t)$ with respect to the time t are given by

$$\dot{X}(t) = A\ \omega\ \cos(\omega\ t)$$

$$\ddot{X}(t) = -\,A\ \omega^2\ \sin(\omega\ t)$$

Hence the differential equation for the harmonic oscillation is given by

$$\ddot{X}(t) = -\,\omega^2\ X(t)$$

The energy E of the an oscillation is the sum of potential and kinetic energy:

$$E(t) = \frac{1}{2}\omega^2 X^2(t) + \frac{1}{2}\dot{X}(t)^2$$

And for an harmonic oscillation, this term is independent of the time t:

$$E = \frac{1}{2}\ A^2\omega^2$$

The more general case of a damped oscillation is given by the differential equation

$$\ddot{X}(t) = -\,\omega^2\ X(t) - D(t)\dot{X}(t)$$

If the damping term would be constant and larger than 0, the oscillation will calm down and its energy will vanish. For the application in this paper an oscillation that will evolve to a medium energy level $\bar{E}$ is required. Therefore, a suitable choice for the damping term is given by

$$D(t) = \frac{1}{A^2\omega}(E(t) - \bar{E})$$

The factor $\frac{1}{A^2\omega}$ in this equation was chosen such that the terms $\omega^2\ X(t)$ and $D(t)\dot{X}(t)$ in the differential equation of the damped oscillation have the same units and order of magnitude ($A\omega^2$). If the current level of energy is less than $\bar{E}$, the term $D(t)$ becomes negative and the oscillation will be intensified.

Application to forecasting a shortwave IMF

In the case of a shortwave IMF, the wave has a clearly shorter wavelength than the timespan on which the EMD has been performed. Hence it is quite easy to obtain the average wavelength and the average amplitude of the oscillation. To determine the average amplitude A, one can take the mean over the absolute values of the IMF at its local extrema. The average wavelength λ can be observed by averaging the distance of adjacent local maxima and the distance of adjacent local minima. Hence, the angular frequency $\omega = \frac{2\,\pi}{\lambda}$ as well as the average energy $E = \frac{1}{2}\ A^2\omega^2$ of the IMF are also known. Since the value of the IMF and its first derivative are numerically known at the right boundary, one can use the formulas of the previous excursus to compute the current level of the energy, the damping function, and the differential equation to forecast the IMF. This differential equation must be solved numerically to forecast the IMF by any standard method.

As a remark, one can obtain the amplitude and the frequency of the IMF instead of the simple statistic suggested in this section also by a Hilbert transform of the IMF.

Forecasting a longwave IMF

To forecast a longwave IMF, the key assumption is that the wave will vary in amplitude or frequency only slowly. Hence, it will be a good approach to forecast the IMF using a pure harmonic oscillation. Therefore, the recent past of the IMF, which is one year throughout this paper, will be approximated by a harmonic oscillation. This harmonic oscillation is used to forecast the IMF.

Earlier, a special case of the harmonic oscillation was already presented, but now the phase of the oscillation is also needed. Hence, the equation for the harmonic oscillation with arbitrary phase is given by

$$X(t) = A \sin\left(\frac{2\pi}{\lambda} t\right) + B \cos\left(\frac{2\pi}{\lambda} t\right)$$

To approximate the IMF with a harmonic oscillation, the least square error function L should be minimized. Let t_i denote the trading days at which the harmonic function should be fitted to the IMF. Then, the function L is given by

$$L(A,B,\lambda) = \sum_{t_i} \left(A \sin\left(\frac{2\pi}{\lambda} t_i\right) + B \cos\left(\frac{2\pi}{\lambda} t_i\right) - \mathrm{IMF}(t_i) \right)^2$$

For each fixed λ, the minimizing values $\hat{A}$ and $\hat{B}$ can be determined by the least square approach. Hence, the derivative with respect to A and B must be 0:

$$\frac{\partial L(A,B,\lambda)}{\partial A} = 2 \sum_{t_i} \left(A \sin\left(\frac{2\pi}{\lambda} t_i\right) + B \cos\left(\frac{2\pi}{\lambda} t_i\right) - \mathrm{IMF}(t_i) \right) \sin\left(\frac{2\pi}{\lambda} t_i\right) = 0$$

$$\frac{\partial L(A,B,\lambda)}{\partial B} = 2 \sum_{t_i} \left(A \sin\left(\frac{2\pi}{\lambda} t_i\right) + B \cos\left(\frac{2\pi}{\lambda} t_i\right) - \mathrm{IMF}(t_i) \right) \cos\left(\frac{2\pi}{\lambda} t_i\right) = 0$$

This is a linear system in A and B, and for its solution the following equation holds:

$$\begin{pmatrix} \sum_{t_i} \sin^2\left(\frac{2\pi}{\lambda} t_i\right) & \sum_{t_i} \sin\left(\frac{2\pi}{\lambda} t_i\right)\cos\left(\frac{2\pi}{\lambda} t_i\right) \\ \sum_{t_i} \sin\left(\frac{2\pi}{\lambda} t_i\right)\cos\left(\frac{2\pi}{\lambda} t_i\right) & \sum_{t_i} \cos^2\left(\frac{2\pi}{\lambda} t_i\right) \end{pmatrix} \begin{pmatrix} \hat{A} \\ \hat{B} \end{pmatrix} = \begin{pmatrix} \sum_{t_i} \mathrm{IMF}(t_i) \sin\left(\frac{2\pi}{\lambda} t_i\right) \\ \sum_{t_i} \mathrm{IMF}(t_i) \cos\left(\frac{2\pi}{\lambda} t_i\right) \end{pmatrix}$$

This linear system is easy to solve since the inverse of the matrix $\begin{pmatrix} X & Z \\ Z & Y \end{pmatrix}$ is given by $\frac{1}{XY-ZZ}\begin{pmatrix} Y & -Z \\ -Z & X \end{pmatrix}$.

Hence, to minimize the function $L(A,B,\lambda)$, it is sufficient to minimize the function $\hat{L}(\lambda) = L(\hat{A}(\lambda), \hat{B}(\lambda), \lambda)$, where $\hat{A}(\lambda)$ and $\hat{B}(\lambda)$ are determined as described above to minimize $L(A,B,\lambda)$. The minimization of $\hat{L}(\lambda)$ can be performed as a one-dimensional minimum search (e.g., by the Golden Section Search) (Press and others 1992).

Forecasting the trend

The forecast of the trend component is done by a straight line, which is pegged to the endpoint of the IMF, denoted by IMF(T), and let T be the last available trading date. To estimate the slope S of this line, a least square fit is performed on the trading days of the last year t_i and the result is given by:

$$S = \frac{\sum_{t_i<T} \left(\mathrm{IMF}(t_i) - \mathrm{IMF}(T)\right)(t_i - T)}{\sum_{t_i<T} (t_i - T)^2}$$

Applications

Study on the price projections on the S&P 500

In the previous section, the technique for forecasting the price based on the EMD was presented. Now this procedure is applied to the S&P 500 index for the past years of this century. For each year, the last trading day of the previous year with a stable decomposition determines the starting point for the prediction—based on a 10-year price history used in the EMD. One should keep in mind that the forecast is just a basis scenario for the price development in the following year, under the assumption that the IMFs will proceed with their current characteristics. A change in waves, especially an increase in amplitude or wavelength, cannot be covered by the presented prediction method.

In Table 3, the forecasted and the actual annual return are shown; even though the differences may be quite large, there is a positive correlation of 33% between the forecast and the actual return. To understand how the price projection can be used, three example years are presented in detail: A quite good, a middle-rate, and a worse forecast year is chosen to explain the results.

Table 3. Forecast and Actual Annual Return of the S&P 500

Year	Annual return Forecast	Annual return Actual	Year	Annual return Forecast	Annual return Actual
2000	-1,8%	-8,8%	2010	26,8%	11,7%
2001	3,1%	-13,0%	2011	-41,2%	-0,7%
2002	3,3%	-23,1%	2012	3,3%	12,2%
2003	23,6%	26,2%	2013	-7,6%	29,9%
2004	10,9%	10,6%	2014	-10,0%	13,0%
2005	8,7%	2,9%	2015	-6,5%	-0,8%
2006	-29,5%	13,1%	2016	-8,1%	8,5%
2007	-1,2%	3,5%	2017	-4,2%	18,9%
2008	-12,9%	-41,2%			
2009	63,3%	26,5%			
Correlation	33%				

Figure 8. S&P 500 and the Forecast for 2003

For the year 2003, the price forecast was given by a slightly upward trend with small corrections (Figure 8). The actual price performed a correction in the first quarter, which was more intense than projected. After the price reached the support level at 800 points, the subsequent upward trend was close to the price projection. The base scenario of 2003—an upward trend without larger corrections—was forecasted very well.

For the year 2016, the projection shown in Figure 9 could be described as sidewise in the first half of the year, with a correction in summer, and in total, a year with a small loss in the equity market. The actual price development was sidewise in the first half, but the summer correction was not so severe, and there was an unexpected rally in the end of the year. Hence, for the total year 2016, the forecast was not that good. The wave that was responsible for the correction became shorter and of less magnitude, which explains the estimation error.

Figure 9. S&P 500 and the Forecast for 2016

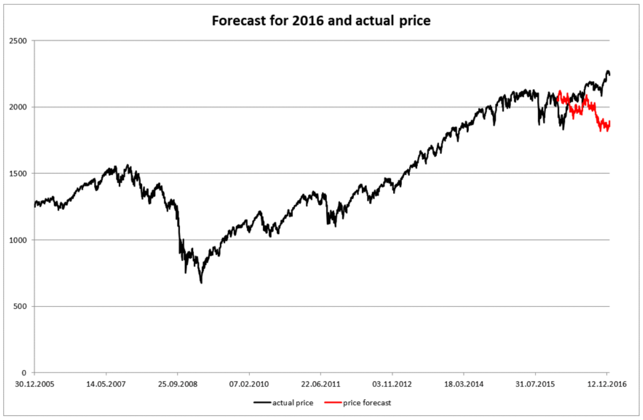
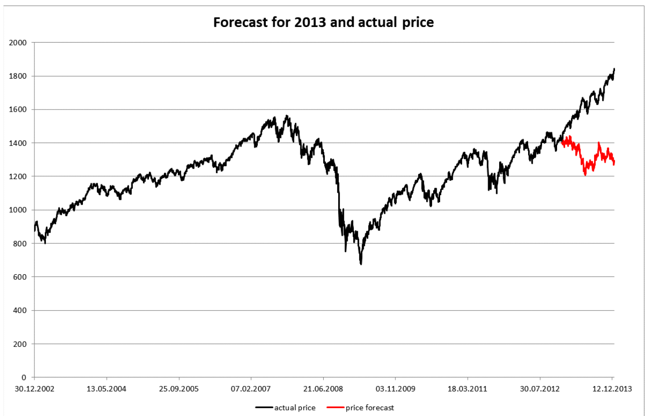


Figure 10. S&P 500 and the Forecast for 2013



The forecast was even worse for the year 2013, as shown in Figure 10. Due to the upward trend since 2009 being quite bumpy, such behavior was extrapolated to the future. But, the waves being relevant for the corrections became smaller, and the long-term wave increased in magnitude and wavelength; the upward trend increased more steadily, and the gap between the forecast and the actual price became quite large. So, if a technical analyst would have provided an outlook based on the EMD for the year 2013, it must have been updated, as it becomes clear that the underlying wave pattern is changing.

Not only for the years 2013 and 2016, but in most cases where larger discrepancies occur, often a wave becomes larger by wavelength and/or amplitude. Keeping this in mind, the technical analyst can formulate a basis scenario based on the EMD and the forecast of its oscillations as described, but he always has to monitor whether the underlying waves alter their characteristics.

Two trading systems based on the EMD

As a second application of the EMD, two profitable trend-following trading systems on the S&P 500 will be presented and compared to the buy and hold approach. Both systems either invest in the index or hold only cash and generate signals if the EMD is stable. The two systems are given by the following:

1) The EMDMA-algorithm buys the index if the EMDMA(6) is rising, where the EMD is performed each trading day on a 10-year history. The position will be closed if the EMDMA(6) is falling. Hence, this system is linked to the earlier discussion on the properties of the EMDMA.
2) The second system makes use of the idea of following the mid-term trend. Since the EMD can be used to eliminate the price oscillations given by the IMFs, a position is bought if the trend component of the EMD is rising, and the position is closed if the trend component is falling. For this system, the EMD is performed each trading day on a 3-year history.

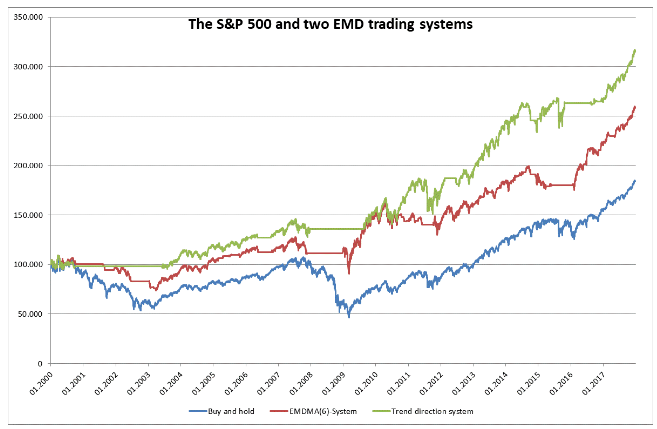
The buy-and-hold approach and the two trading strategies are back tested in the period from 2000 to 2017, each with a starting capital of $100,000 USD. The results are listed in Table 4, and the equity curve of the three systems is shown in Figure 11. It is clear that the two EMD-based systems are superior to the buy-and hold approach as well as to the return as to its risk, measured by the maximum drawdown.

Table 4. Comparison of Two Trading Strategies With Buy-and-Hold on the S&P 500 Index

	Buy and hold	EMDMA system	Trend direction system
Start capital	100.000,00	100.000,00	100.000,00
End capital	183.725,48	258.134,88	315.102,15
Annual return*	3,4%	5,4%	6,6%
Maximum Drawdown	56,8%	32,7%	19,4%

* without dividends or trading costs

Figure 11. Equity Curve of the Two EMD Trading Systems and the S&P 500



Conclusion

Charles Dow illustrated the movements of the markets by the tide (primary trend), the large waves (secondary reaction), and the ripples on the water surface (daily fluctuations). Hence, it makes sense to apply research from the field of hydrosphere to technical analysis. The original paper of (Huang and others 1998) on the EMD was developed at several hydrosphere research institutes, and this paper provides a comprehensive discussion on the use of the EMD for technical analysts.

The EMD was previously applied to financial price series by (Dürschner 2014), but there was still the need for further adaptions to match the needs of technical analysts. This paper imposes additional specifications to stabilize the decomposition. At first, additional supporting points at the boundary are introduced to stabilize the sifting process. Secondly, the terminating condition of the sifting iterations is expressed explicitly, and such that the decomposition becomes more stable with regard to the shift of the timeframe. The latter is quite important for applications in trading systems, as the decomposition as of yesterday should be similar to the decomposition as of today.

The presented EMD technique could also be used to determine a price forecast based on the identified waves in the price (Reiss 2017). The basic idea of this approach is that the IMFs are waves that can be extrapolated by the mathematics of oscillations. As a result, one can obtain a basis scenario for the price projection based on the assumption that the characteristics of the waves remain stable. These projections are studied on the S&P 500 index, and two trading systems based on the EMD are presented that are more profitable and less risky than the buy-and-hold approach.

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Data and Software

The market data used for this research have been obtained by the software TAI-PAN End-of-Day from the provider Lenz+Partner GmbH (www.lp-software.com), which is part of the vwd group (www.vwd.com).

"Chasing SKURT Signals"

A New Statistical Method for Determining Trend Changes and Timing Trades

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Abstract

In this paper we propose a trading method using price skewness and kurtosis that we call the "SKURT signal." The SKEW index provided by CBOE indicates whether the stock price distribution is biased toward an increase or decrease. The former suggests stock prices are rising; the latter suggests they are falling. That is, SKEW can be used as a statistical indicator for measuring price direction. In addition, KURT is an index indicating whether the distribution of prices is concentrated or dispersed. If the distribution is concentrated, it suggests that there is a trend, and if the distribution is dispersed, it suggests that the trend is not clear. In other words, KURT can be used as a statistical indicator to measure the presence or absence of a trend. In this paper, we generate a trading signal by combining these two statistical measures and investigate the effectiveness of the actual trades. If SKEW suggests a rise in price and KURT suggests a trend, it is a buy signal; and if SKEW suggests a decline in price and KURT suggests the presence of a trend, it is a sell signal. We have named this combined SKEW and KURT signal "SKURT." Using this method, we confirm the validity of SKURT in 14 indexes and discuss the results.

Introduction

Background

This is a statistical expansion of "Entropy of Market Profile", an MFTA paper submitted by the author. That paper focused on the distribution of intraday prices, but here we focus on long-term price distribution for long-term investors and devise a new indicator for timing trades. In this paper we aim to statistically capture market biases and appearances, disappearances, and changes in trends. SKURT can be calculated with Microsoft Excel and will generate signals that individual investors can act on themselves.

SKEW and KURT

Although indexes such as VIX and IV (implied volatility) are used as indices of uncertainty in the market, because VIX is an indicator that suggests the magnitude of price fluctuation risk, it has difficulty capturing risk bias and long-term fluctuation risk. In addition, we found it difficult to use as a long-term indicator when comparing it to the stock price charts. In recent years, to complement this, SKEW, which captures the tail risk bias of the market, has attracted attention, and CBOE provides an indicator called the SKEW Index. It represents the skewness (distribution bias) of the S&P 500. It is similar to VIX in its usage. The SKEW Index indicates whether the distribution of prices is biased to the left or right compared with the normal distribution. The price is biased to the downside if the SKEW is right-biased (>=) compared with the normal distribution, and the price is biased to the upside if the SKEW is left-biased (<=).

Figure 1. SKEW and Standard Deviations

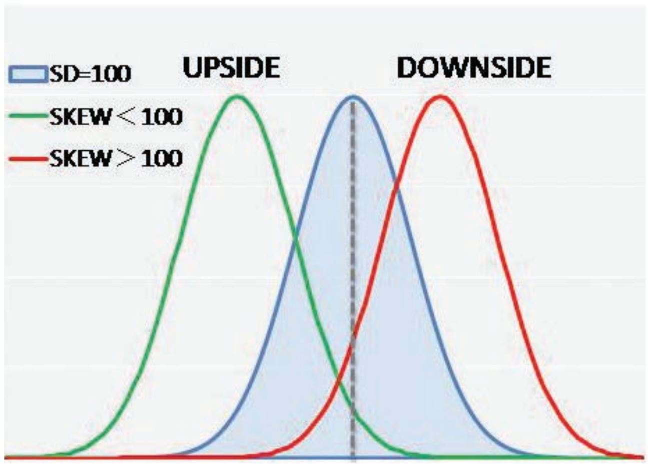


Figure 2. FTSE 100 and SKEW

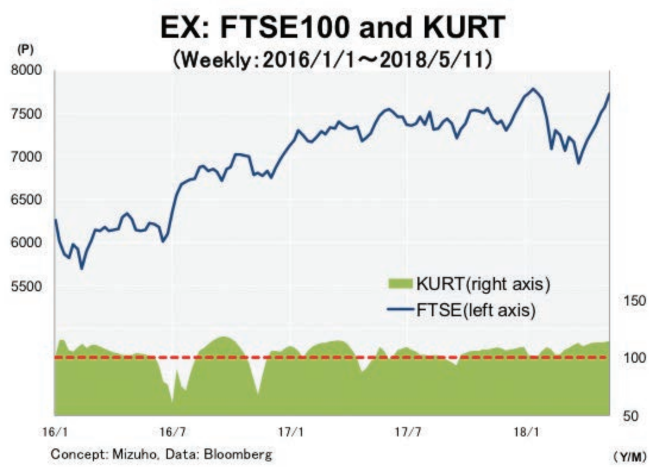


Figure 3. KURT

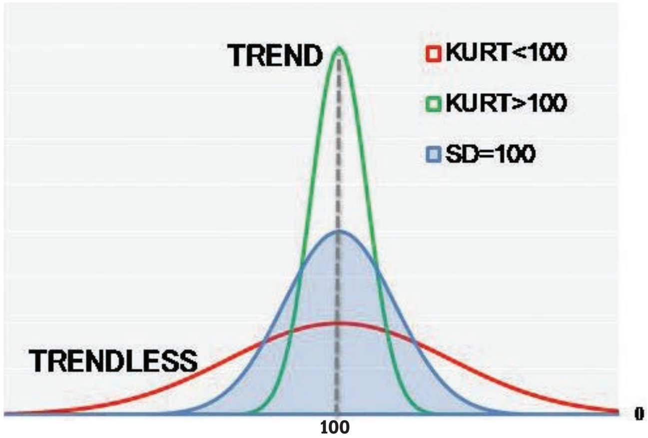
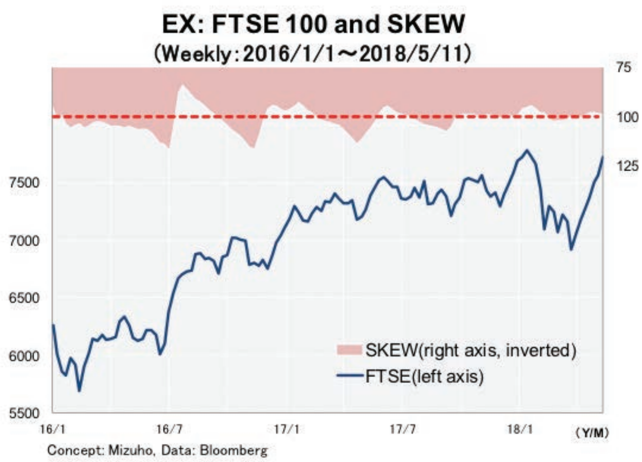


Figure 4. FTSE 100 and KURT



Therefore, using the same formula as CBOE's SKEW Index, we altered the index parameters (n ≥ 20) for long-term investment; rebased the S&P 500, Eurostoxx 50, TOPIX 100, and other indexes to 100; and back-tested them (see Figure 2). However, we thought that the resulting performance was low when we used the SKEW index alone to generate trading signals, and we decided that complementary indicators were necessary. Therefore, we were able to measure the market's bias by statistically analyzing whether its price distribution was concentrated or dispersed, using skewness and its conceptual opposite, kurtosis. If KURT is more positive than a normal distribution, then a trend is present, and if it is negative, then the price action is determined to be trendless. Therefore, we tried to combine these two indicators to generate trading signals.

Methodology

Concept

When SKEW and KURT are combined, it generates a matrix like that in Figure 3, and the timing of trades is as follows. This indicator can be applied in all cases (long-term, short-term), (long-buy, short-sell), but in this paper, we first try to use it to generate signals for long-term investment.

Formula

To make it easier to see the calculated SKEW and KURT indicators, we rebased each index to 100.

$$\mathrm{SKEW} = 1 - \frac{n}{(n-1)(n-2)} \sum \left(\frac{x_i - \overline{x}}{s}\right)^3$$

$$\mathrm{KURT} = 1 - \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \overline{x}}{s}\right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

(Note) N = 20, unit is displayed (%)

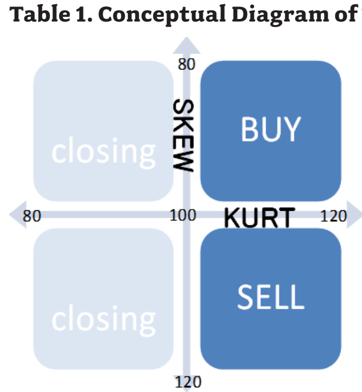
Test Data

Weekly: January 1990—May 11, 2018
14 Indexes
Stocks: Nikkei 225, TOPIX, S&P 500, DAX, FTSE 100, EUROSTOXX 50
Currency: Dollar Yen, Euro Dollar, Dollar Euro,
Bonds: 10-year U.S. government bonds, 10-year Japanese government bonds, German government bonds
Commodities: NY Gold, WTI Crude Oil

Trading Method

Buy: When SKEW <100 (indicating a rise) and KURT >100 (suggesting a trend), a buy occurs at the opening price of the following week.
Sell: When either SKEW or KURT turns neutral, a sell occurs at the opening price of the following week.
Add optimization if necessary.

Table 1. Conceptual Diagram of Trading Method



Results

Results of backtesting the SKURT signals with 14 indexes are as follows.

First, SKURT is suitable for stock markets; it is less reliable in other markets. In order of effectiveness: GOLD, DAX, EUROXX 50, WTI crude oil, S&P 500.

Table 2. Performance Ranking Result

Test priod: 1990/1/5–2018/5/11	WINNING TRADES				LOSING TRADES				ALL TRADES								
	Trades (No.)	Total return (%)	Avg. return (%)	Avg. hold (days)	Trades (No.)	Total return (%)	Avg. return (%)	Avg. hold (days)	Trades No.	Total return (%)	Avg. return (%)	Avg. hold (days)	Win rate (%)	Profit factor (ratio)	Risk/reward (ratio)	Draw down (%)
GOLD	3	384	128.1	1881	3	−27	−9.1	1122	6	357	59.5	1502	50	14.1	14.1	−20
DAX	11	307	27.9	708	2	−18	−9.0	56	13	289	22.2	608	85	17.1	3.1	−59
EUROSTOXX50	10	318	31.8	642	5	−44	−8.8	144	15	274	18.2	476	67	7.2	3.6	−30
WTI	4	261	65.4	1521	2	−34	−16.9	896	6	228	38.0	1313	67	7.8	3.9	−57
S&P500	12	231	19.3	482	5	−79	−15.8	199	17	152	9.0	399	71	2.9	1.2	−41
FTSE100	9	184	20.4	589	6	−72	−12.0	203	15	112	7.5	434	60	2.6	1.7	−31
DAW	10	192	19.2	506	7	−81	−11.5	264	17	111	6.5	406	59	2.4	1.7	−29
NKY	9	315	35.0	531	13	−216	−16.7	583	22	99	4.5	562	41	1.5	2.1	−59
GERMNBND	9	64	7.1	825	4	−17	−4.3	151	13	47	3.6	618	69	3.7	1.6	−16
USD/JPY	6	108	17.9	645	10	−71	−7.1	293	16	36	2.3	425	38	1.5	2.5	−19
TOPIX	6	102	17.0	803	6	−73	−12.2	306	12	28	2.4	554	50	1.4	1.4	0
USD/EUR	4	70	17.5	1689	5	−42	−8.4	312	9	28	3.1	924	44	1.7	2.1	−16
EUR/USD	6	77	12.8	672	7	−50	−7.1	467	13	27	2.1	562	46	1.5	1.8	−20
UST	7	47	6.8	758	4	−21	−5.3	590	11	26	2.4	697	64	2.2	1.3	−8
JGB	7	36	5.2	503	9	−20	−2.3	184	16	16	1.0	329	44	1.8	2.3	−7
Avg.	8	180	28.7	850	6	−58	−9.8	385	13	122	12.1	654	57	4.6	3.0	−28

Concept: Mizuho, Data:Bloomberg

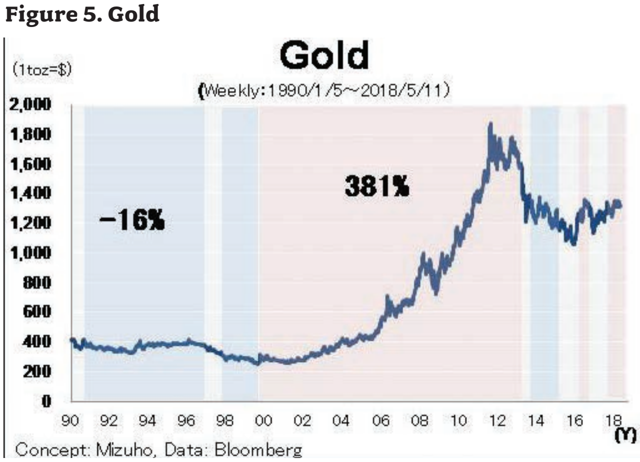
Gold

Table 3. Gold

GC	Buy Date	Buy Price	Sell Date	Sell Price	Return(%)	Hold (days)	Draw down(%)
1	1990/10/5	419	1997/7/25	328.8	−16.8	2485	−20
2	1998/3/13	495	1999/1/8	289.6	−1.7	301	−8
3	1999/11/19	1241	2013/4/26	1406.8	381.6	4907	−13
4	2013/12/27	1359	2015/7/31	1098.6	−8.8	581	−11
5	2016/3/4	1404	2016/6/10	1244.4	1.7	98	−2
6	2016/7/29	1502	2018/4/27	1334	0.9	637	−15

Concept: Mizuho, Data: Bloomberg

Figure 5. Gold



Of the 14 indexes, the highest total revenue generated according to the back-test results of the SKURT signals since 1990 was NY gold. Blue indicates periods of loss and red indicates periods of profit. Gold generated clear trends. Since 1990, it has generated three wins and three losses out of six trading opportunities. The red part in the middle of Figure 5 was the most profitable period, and the holding period lasted as long as 13 years. The average rate of return per round trip was 60%.

DAX

Table 4. DAX

DAX	Buy Date	Buy Price	Sell Date	Sell Price	Return(%)	Hold (days)	Draw down(%)
1	1990/5/25	1831.26	1990/8/24	1680.56	-8.2	91	-9.0
2	1991/2/8	1434.24	1992/5/22	1744.71	21.6	469	-1.0
3	1992/7/10	1775.99	1992/7/31	1602.6	-9.8	21	-9.5
4	1993/3/12	1678.87	1995/2/10	2086.21	24.3	700	-4.7
5	1995/3/10	2086.8	2001/3/30	5557.82	166.3	2212	-9.3
6	2002/3/29	5361.2	2008/2/1	6749.29	25.9	2135	-59.2
7	2009/8/28	5464.53	2009/11/27	5689.38	4.1	91	-3.7
8	2010/2/12	5476.47	2011/8/12	6170.69	12.7	546	-0.8
9	2012/3/2	6817.46	2013/4/5	7806.12	14.5	399	-13.2
10	2013/6/14	8246.04	2015/9/4	10200.98	23.7	812	-7.2
11	2016/9/2	10503.88	2016/11/18	10750.62	2.3	77	-3.1
12	2017/1/20	11537.45	2017/4/21	12135.61	5.2	91	-1.0
13	2017/5/5	12478.46	2018/1/19	13244.37	6.1	259	-4.9

Concept: Mizuho, Data: Bloomberg

Figure 6. DAX

The second-place performer was the DAX index. It generated 13 trading opportunities from 1990—11 wins and two losses. The winning percentage was high at 85%, but the drawdown was the largest among the 14 indicators. The greatest loss was 59% during the 2008 financial crisis. (In fact, one would probably not have continued holding in this case.) The average return per trade was 22%.

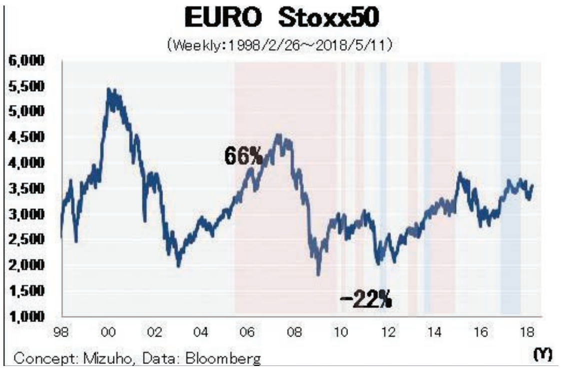
EUROSTOXX

Table 5. EUROSTOXX 50

SX5E	Buy Date	Buy Price	Sell Date	Sell Price	Return(%)	Hold (days)	Draw down(%)
1	1990/6/22	362.91	1991/5/31	377.54	4	343	-19
2	1991/8/2	380.93	1992/4/24	416.05	9	266	-3
3	1993/1/8	435.7	1993/12/31	467.4	7	357	-2
4	1994/2/18	470.18	1994/4/8	445.66	-5	49	-7
5	1994/8/12	457.08	1998/9/11	973.89	113	1491	-3
6	1999/5/14	1345	2001/3/30	1139.83	-15	686	-20
7	2001/8/31	1184.93	2001/9/28	965.8	-18	28	-20
8	2003/6/20	988.61	2005/3/4	1211.37	23	623	-3
9	2005/4/1	1171.42	2006/3/10	1287.23	10	343	-3
10	2006/4/14	1295.51	2008/2/1	1330.7	3	658	-6
11	2008/5/23	1425.28	2008/10/17	912.75	-36	147	-41
12	2009/8/28	1026.59	2009/11/27	1094.86	7	91	-3
13	2010/4/16	1194.94	2011/8/12	1198.48	0	483	-15
14	2011/12/16	1255.05	2014/2/28	1836.78	46	805	-4
15	2014/3/14	1877.86	2014/11/7	2018.21	7	238	-3
16	2015/3/20	2055.35	2015/6/19	2091.34	2	91	0
17	2016/8/19	2186.08	2016/11/11	2100.59	-4	84	-5

Concept: Mizuho, Data: Bloomberg

Figure 7. EUROSTOXX 50



In third place was Euro Stoxx 50: 10 wins and five losses since 1990. The average return was 18%, the RRR (Risk/Reward Ratio) was 3.6, which is high, and the most recent buy signal occurred in February 2018.

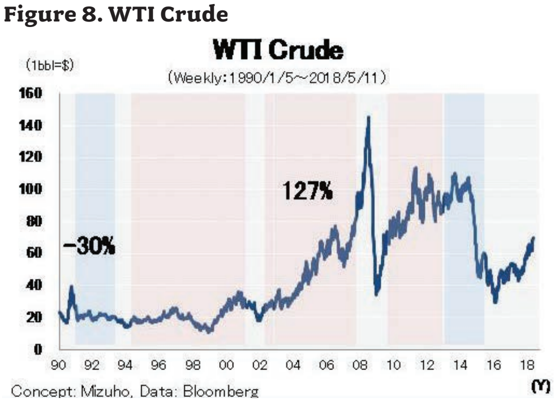
WTI CRUDE

Table 6. WTI Crude

CL	Buy Date	Buy Price	Sell Date	Sell Price	Return(%)	Hold (days)	Draw down(%)
1	1990/9/14	28.6	1993/6/4	19.99	-30.1	994	-39.0
2	1994/3/18	14.44	2001/10/5	23.5	62.7	2758	-28.3
3	2002/2/15	20.27	2002/7/12	26.77	32.1	147	-1.5
4	2002/8/2	26.52	2006/9/29	60.25	127.2	1519	-6.4
5	2007/8/10	75.04	2012/2/24	104.65	39.5	1659	-56.8
6	2012/3/30	106.79	2014/6/6	102.92	-3.6	798	-27.6

Concept: Mizuho, Data: Bloomberg

Figure 8. WTI Crude



In fourth place was WTI Crude. Like NY gold, the long-term trend was clear—the average holding period was relatively long at about four years. The winning percentage was 67%, and the RRR was high at 3.9. However, there were only six signals, generating four wins and two losses.

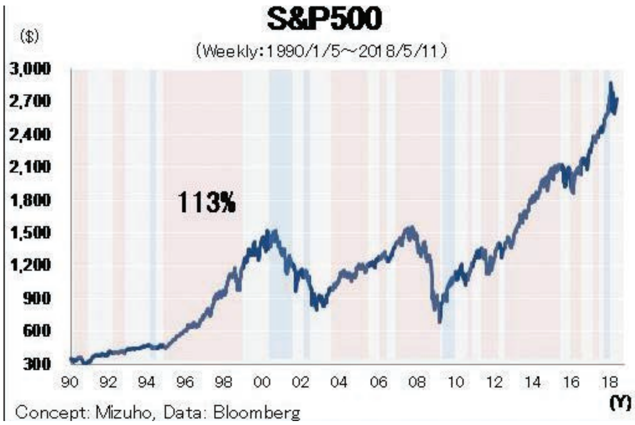
S&P 500

Table 7. S&P 500

SPX	Buy Date	Buy Price	Sell Date	Sell Price	Return(%)	Hold (days)	Draw down(%)
1	1990/6/22	362.91	1991/5/31	377.54	4.0	343	-19
2	1991/8/2	380.93	1992/4/24	416.05	9.2	266	-3
3	1993/1/8	435.7	1993/12/31	467.4	7.3	357	-2
4	1994/2/18	470.18	1994/4/8	445.66	-5.2	49	-7
5	1994/8/12	457.08	1998/9/11	973.89	113.1	1491	-3
6	1999/5/14	1345	2001/3/30	1139.83	-15.3	686	-20
7	2001/8/31	1184.93	2001/9/28	965.8	-18.5	28	-20
8	2003/6/20	988.61	2005/3/4	1211.37	22.5	623	-3
9	2005/4/1	1171.42	2006/3/10	1287.23	9.9	343	-3
10	2006/4/14	1295.51	2008/2/1	1330.7	2.7	658	-6
11	2008/5/23	1425.28	2008/10/17	912.75	-36.0	147	-41
12	2009/8/28	1026.59	2009/11/27	1094.86	6.7	91	-3
13	2010/4/16	1194.94	2011/8/12	1198.48	0.3	483	-15
14	2011/12/16	1255.05	2014/2/28	1836.78	46.4	805	-4
15	2014/3/14	1877.86	2014/11/7	2018.21	7.5	238	-3
16	2015/3/20	2055.35	2015/6/19	2091.34	1.8	91	0
17	2016/8/19	2186.08	2016/11/11	2100.59	-3.9	84	-5

Concept: Mizuho, Data: Bloomberg

Figure 9. S&P 500



The S&P 500 Index was the fifth-best performer. With 12 wins and five losses, the win rate was high at 71%, but the average rate of return was only 9%. The maximum drawdown, which occurred during the financial crisis of 2008, was relatively high at 41%.

Discussion

We discuss three points. The first one is stop losses. In actual trading, stop losses are necessary. For example, to protect capital, it may not be realistic to keep holding positions that lose a certain percentage, such as 20%. If we were to impose stop-loss rules on the trading method, it could reduce the size of large drawdowns. The second point concerns the parameters. In this case, n = 20 was used to obtain signals for long-term investment, but it could be necessary to change the parameters to reflect the trade's expected duration. If the trade is based on short-term daily data, then it would seem preferable if n = 5 or 7. Thirdly, it's possible that performance could improve by permitting both long buys and short sells. However, since SKURT has a delayed effect when selling, it may be necessary to use daily or intraday data. Also, in that case, it seems it would be necessary to optimize the method's parameters and trading rules for each market.

Conclusion

All told, SKURT's success rate over 201 trades was 57%. In terms of total revenue, commodities and stocks were most effective, followed by currency and bonds. Comparing asset classes, SKURT seems to be most suitable for stocks and commodities. The average rate of return per transaction was 10% for equities and 49% for commodities during the period. It can be said that SKURT is an effective indicator of trends and generator of timing signals. However, in fact, further consideration is necessary. In the future, I would like to try to improve the results by adding trade conditions such as stop losses and short-sell positions. In addition, we conducted a long-term back test using weekly data from 1990 this time. In the future, we will change the timeframe and parameters and add some other conditions. We hope that these considerations will provide individual investors with a reliable trading indicator.

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Software and Data

Bloomberg Data

Microsoft Excel

Geometric Patterns in Commodity Price Data —Crop Circles or Actionable Information?

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Abstract

Currently, in practical applications, the recognition of patterns within the price histories of traded securities is entirely reliant upon visual identification. Due to the time-consuming nature of this identification process, it is difficult to know if charting patterns accurately predict price trend movements. We developed a method that automates recognition of charting patterns within a dataset, combining both the objective elements of pattern definitions with the subjective nature of their visual identification, to create an efficient means for analyzing the predictive effectiveness. This method is employed on the historical trading prices of 17 different commodities (from January 1980 to December 2013). Additionally, we evaluated a chart pattern against the "ideal" chart pattern, to see if patterns closer to ideal have more predictive success. We also tested differing window time spans, and differing back-trend lengths. All were evaluated using Rank-Sum tests, and none were statistically significant.

Introduction

Lo, Mamaysky, and Wang (2000), in the seminal article regarding automated pattern recognition in financial time series data, state that "…it may be possible to determine 'optimal patterns' for detecting certain types of phenomena in financial time series…" (page 1753). Pattern recognition, more colloquially known as "charting,"[1] involves the visual study of financial time series data, typically price (as well as volume), in an attempt to determine the direction of future price changes (Murphy 2001). The ultimate goal is to use this knowledge in an attempt to generate positive alpha.

Charting has been widely applied by investors, while also being the subject of significant academic study. There is an innate conflict between the two parties, however, as security traders believe that proper implementation of charting pattern analysis in an investment strategy can lead to significant profit, while academic studies remain very skeptical of the actual predictive capabilities of patterns found in notoriously volatile, or "noisy" price history data. Typically, known patterns are said to predict price changes, resulting in buy or sell signals that chartists will use to guide their investment decisions. The identification of charting patterns in real-world applications occurs as chartists watch the movements of a given traded security's price movements, waiting for a known pattern to appear (e.g., a rounding top). However, this visual recognition process is almost entirely subjective, and while one chartist may consider a subsection of a security's price history to be a known formation, another may disagree. The common refrain is that charting, and more broadly technical analysis, is both science and art.

Meanwhile, the process of manually identifying charting patterns is a time-consuming task, and therefore, collecting data concerning instances of these patterns is incredibly difficult. This leads to an inability to thoroughly study the effectiveness of these patterns as indications of price trend changes. Walter Deemer, in Lo and Hasanhodzic (2009), indicates the importance of automating this process, when noting that traders would be able to quickly sift through data, using "…the computer to flag them." The value of an efficient, automated method for charting pattern recognition can easily be seen when comparing the amount of data that can be analyzed by a computer versus a human. It would take weeks for a trained technical analyst to locate patterns in several years of trading price data, whereas, presumably, the correct development of an automated process could take merely seconds or minutes. This drastic improvement in the efficiency of data collection vastly expands the potential for more in-depth academic research of the predictive capabilities of charting patterns and, correspondingly, the potential profitability of investing strategies that implement them.

In this paper, we utilize software to develop an automated, efficient pattern recognition process. John J. Murphy, when asked about the effectiveness of charting, neatly summarized the issues: "…I've never gone back and done a historical study. It's very hard to do quantitative analysis of chart patterns, because they are somewhat subjective…It's very hard to teach a computer to read a chart pattern." (Lo and Hasanhodzic, 2009) The question we tackle is how do you get a computer to mimic the function performed by the human eye? We then use the software to identify one of the most oft-cited charting indicators, the head-and-shoulders pattern, in commodity price data. Previous studies have used stock price data and foreign currency data; however, Murphy (1999) notes that technical analysis may be especially suited for commodity applications because there are no additional revenue streams (dividends). Returns for investors, or speculators, in commodities are generated by correctly determining the direction of prices alone. As such, we use our developed program to test various hypotheses, as it applies to the efficacy of the head-and-shoulders and inverse head-and-shoulders pattern. Specifically, we develop the "ideal" head-and-shoulders and inverse head-and-shoulders pattern, and then test several hypotheses to determine the efficacy of the pattern as it relates to identifying a reversal in price trends. We find that in all cases but one, head-and-shoulders and inverse head-and-shoulders patterns successfully identify a reversal in the trend more than 50 percent of the time. However, given how we define a trend in a price series for purposes of coding, it is not practical to extrapolate these results into trading outcomes stated in terms of dollars gained or percentages earned. We are unable to show that more specific criteria improve the efficacy of the pattern as it pertains to accurately predicting a trend reversal.

Issues

Technical analysis is rooted in the analysis of price and volume to uncover information regarding the future direction of a security's price. Murphy (1999) (page 2) says it in his book: "1. Market action discounts everything. 2. Prices move in trends. 3. History repeats itself." Technical analysis relies on the patterns in trading price histories, seeking to identify current price trends and the points at which the current trend will reverse itself. Many trading strategies based on technical analysis use a combination of metrics, including moving averages, price channels, levels of support and resistance, and chart analysis, to identify as early as possible, the buy and sell signals resulting from these points of trend reversal. Murphy (1999) argues that all analysis of time series data uses past events as a predictor, or explanatory variable, and studying charts is no different.

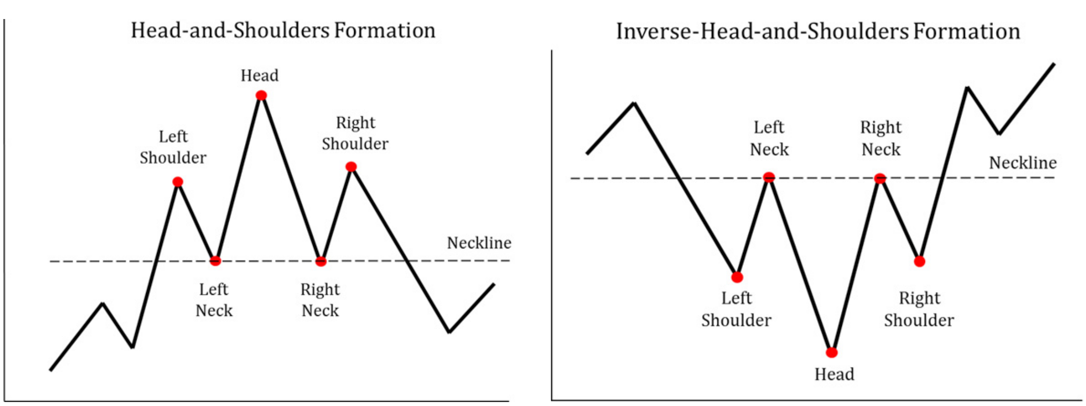
Charting Patterns

Some of the most widely used technical indicators are charting patterns that periodically appear in the price movement of a security. Typically, these charting patterns are various combinations of five relative extrema, or maxima and minima. The identification of these charting patterns is very subjective since no two chart formations will be exactly alike, and the characterization of each formation is loosely defined. This leaves the recognition of chart formations reliant on not only the science of technical indicators, developed from financial study, but also on the art, manifested by each interpreter's view of what constitutes a distinguished pattern. The two patterns of interest in this study are the two most widely accepted trend reversal patterns: the head-and-shoulders and inverse head-and-shoulders formations.

Paul Desmond (Lo and Hasanhodzic, 2009), John Murphy (1999, 2001), Lo and Hasanhodzic (2010), and others have made the psychological argument for why both head-and-shoulders and inverse head-and-shoulders charts should work as a trading tool. Assume that a security is currently exhibiting an uptrend. The direction is dictated by the imbalance between the number of buyers and sellers; in this case, there are more buyers, or buyers with more conviction. As a trend potentially nears its end, this imbalance begins to correct. Lo and Hasanhodzic (2010) describe it as such, saying, "As the sellers come in and test the downside market potential, the prices are brought down, leaving behind a peak corresponding to the 'left shoulder.'" (page 94) This is the point where prospective buyers, not realizing the potential end to the imbalance, step in and buy what they think is a temporary price decline. This causes the price to rise higher than its previous high. This is the head. However, with doubts about the conviction of the buyers, sellers again try to test the buyers, again causing a price decline. Buyers try to protect their positions by purchasing again, but buyers are running out of capital or conviction, or both. This short-term increase forms the right shoulder, but once sellers again test the buyers, the end of the trend is complete, and the price pattern reverses.

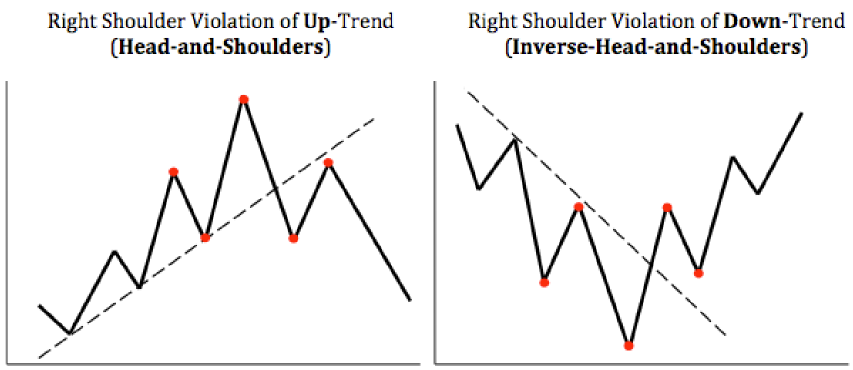
To successfully capture this charting pattern, one must be able to train the computer to recognize this pattern. To illustrate the formations, we will focus mainly on the head-and-shoulders formation, as the inverse head-and-shoulders is simply the mirrored opposite. Mathematically, the head-and-shoulders formation consists of five extrema—three peaks and two troughs—in a security's price history. The middle peak is higher than the outer two peaks, and the troughs are roughly level. The outer peaks are referred to as the left and right "shoulders," the middle peak as the "head," and the connection of the troughs, the "neckline." This, along with the mirrored inverse head-and-shoulders, is displayed in Figure 1.

Figure 1. Head-and-Shoulders and Inverse Head-and-Shoulders Formation



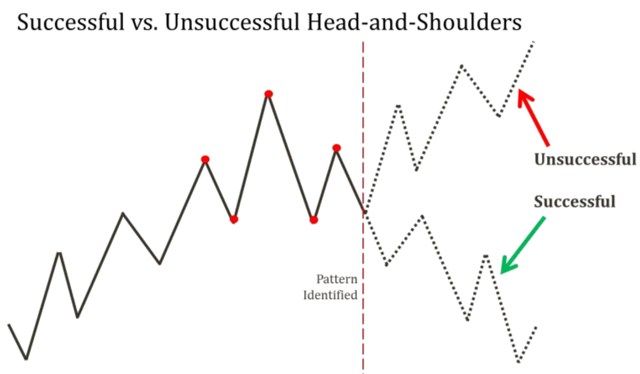
Traders are often heard saying, "The trend is your friend." Continuing with the mathematical description, during an up-trend, the relative minimums of a security's price oscillations form a line of support, as the price bounces off the line in some level of upward movement. A successful head-and-shoulders formation will signal a reversal from an up-trend to a down-trend (series of increasing or decreasing extrema, respectively). The right neck point is the first indication of a potential head-and-shoulders formation, as it has an approximately equal price to the previous minimum (the left neck) and thus breaks the trend of consistently increasing minima. The right shoulder of the head-and-shoulders formation serves as a confirmation of the formation. It is the point at which the upward trend line's level of support is broken, as seen in Figure 2, since the new relative maximum of the security's price fails to rise above the head.

Figure 2. Right Shoulder Violation of Up-trend and Down-trend



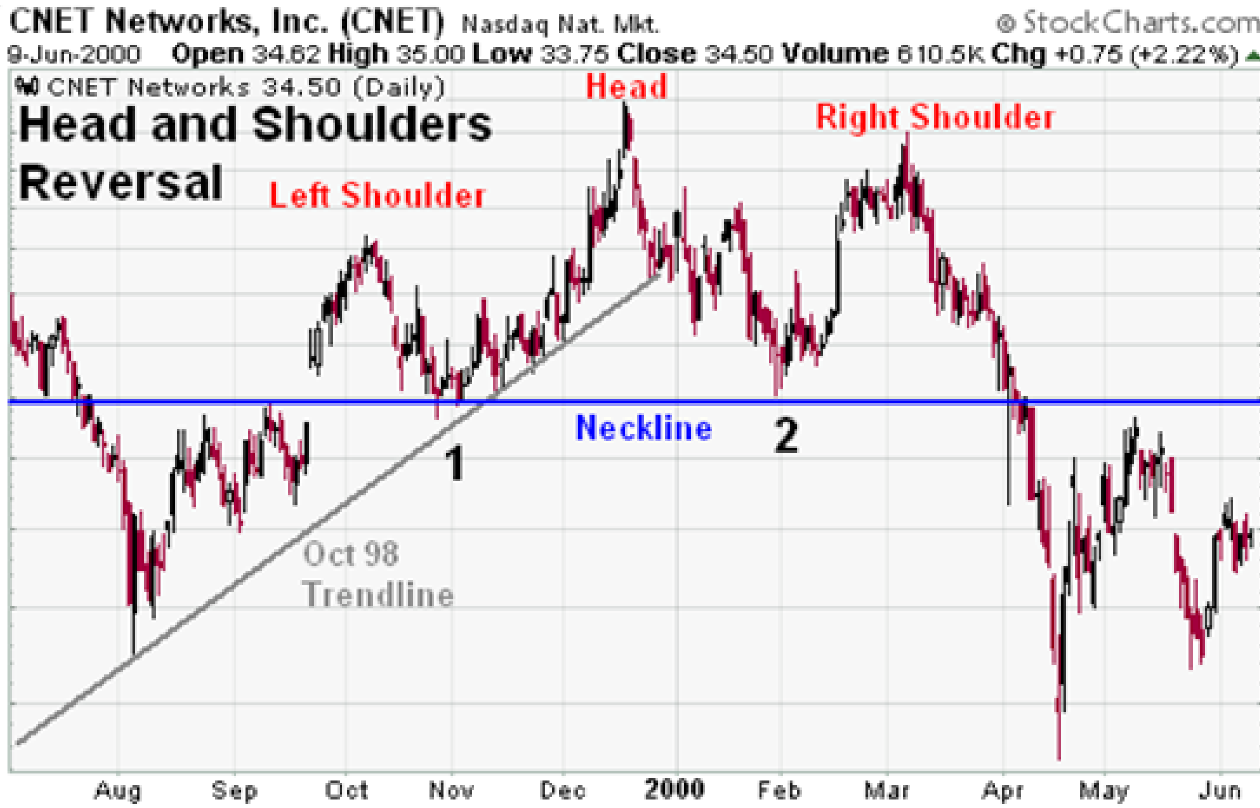
This violation of the up-trend then acts as a signal of an impending down-trend. Similarly for the inverse head-and-shoulders formation, which occurs following a down-trend, the right shoulder is the point at which the level of resistance created by the down-trend is violated, thus signaling a reversal to an up-trend, also shown in Figure 2. Therefore, for a head-and-shoulders formation to be successful, there must be a down-trend following the formation, displayed in Figure 3. Similarly, for an inverse head-and-shoulders formation to be successful, there must be an up-trend following the formation. If the opposite is true in each case, the trend did not reverse and the signal failed.

Figure 3. Successful vs. Unsuccessful Head-and-Shoulders



It is necessary to define head-and-shoulders and inverse head-and-shoulders in broad terms because no traded security, due to the incredible variability or noise in the data, will have perfectly proportionate five sequential extrema. In reality, as displayed by CNET Networks' price history (see Figure 4), there are many other extrema between the points designated as the left shoulder, head, and right shoulder, and the five extrema are certainly not in the exact ideal proportions (i.e., the right shoulder is rather high compared to the left shoulder). Even with these deviations from the ideal proportions, since the pattern meets the loose requirements of a formation, it was designated by a chartist as being a head-and-shoulders formation and indeed appears to have correctly predicted a trend reversal from up to down.

Figure 4. Example of Head-and-Shoulders Formation



Our specific aim for this project is to create an algorithm by which a computer can locate instances of either of these two formations occurring in the price history of several commodities and to recognize the price trend leading into and following the formation. Once identified, the computer can determine certain qualities of that formation (e.g., length, proportions) and, most importantly, whether that formation was successful in predicting a trend change reversal as it theoretically should.

Previous studies that attempt to automate the charting pattern recognition process focus on two types of traded securities: common stock and currency exchange rates. This creates a potential contribution of this study, as we focus only on identifying and evaluating the predictive capability of patterns in historical commodity price data. More importantly, though, is that this study evaluates the characteristics of the formations to see if patterns emerge, such that certain characteristics are more indicative of success or failure.

Method

The medium through which we automate the pattern recognition process is MATLAB, a programming software commonly used by quantitative decision makers across a variety of industries. We encode functions within MATLAB that attempt to mirror the four general processes done visually by a chartist when searching for charting patterns. The first process is to smooth the data through a new approach not tried in previous studies. This smoothing process adds a fine-tuned algorithm that necessarily reduces volatility and detects price movement trends in a manner consistent with how the eye ignores visually insignificant noise in a dataset. Second, a parameterization of the head-and-shoulders and inverse head-and-shoulders formations is done, which allows the computer to account for both the objective definitions of the patterns (based in financial theory) and the subjective nature of the chartists' judgment. Third, a quantification is determined of how ideal a given identified formation is compared to the expected form, which allows analysis of the relative performance of "good" versus "bad" patterns; this is unique to this study. Finally, a dynamic approach to identifying trend lines in price movement is taken, allowing automated recognition of trend reversal, and thus a determination of whether or not a given pattern is accurate in its prediction.

Data

While charting patterns may be applied to a myriad of traded securities, typically studies related to the predictive effectiveness of charting patterns have been conducted on stocks or currency exchange rates: Lo, Mamaysky, and Wang (2000), Levy (1971), and Savin, Weller, and Zvingelis (2007) on US-traded stocks; Dawson and Steeley (2003) on UK-traded stocks; and Chang and Osler (1999) on exchange rates. John J. Murphy, in his discussions with Lo and Hasanhodzic (2009), noted that in a technical analysis course taught by Alan Shaw, Shaw recommended the application of technical analysis on commodity prices. Likewise, Laslo Birinyi (Lo and Hasanhodzic, 2009) notes that technical analysis is more effective when applied to foreign exchange markets and to some commodity markets, noting that most of the analysis consists of analyzing charts. This leaves room for this study's contribution to methods applied to commodities.

Commodities are roughly defined as inputs in the production of other goods or services, ranging from crude oil to wheat.

Traded on exchanges similar to other securities, commodity prices vary as fluctuations in supply and demand determine the relative price. While some chartists use interday or weekly data, daily trading prices dominate the majority of use by real-world chartists as well as pattern recognition studies. Therefore, for this study we used the daily trading data for 17 different commodities.[2] The length of data for each commodity varied, due to availability, from January 2, 1980, to December 31, 2013. Additionally, for some of the historical commodity price data, earlier prices needed to be cut due to a lack of day-to day variation. For example, prior to roughly 11 years ago, the price of hogs did not vary consistently day to day, going in some cases weeks without a change in price. This lack of variation leads to a plateau-like structure of the price history rather than series of relative extrema and thus, is not conducive to charting analysis. All data were retrieved using Thomson Datastream.

Model

Smoothing Algorithm

Before attempting to locate the charting patterns in the commodity price data, we needed to develop a process for locating relative extrema in the historical prices of a security. Identifying the locations of every relative extrema is very simple: find the days in which the price is either higher or lower than the two days surrounding it. However, due to the extreme day-to-day volatility of traded securities, using the explicit definition of a relative extrema leads to an exorbitant number of frivolous points. Any smoothing technique necessary for the automation of pattern recognition must account for some of the subjectivity that is involved with locating charting patterns: the natural tendency of the eye to smooth out the unnecessary variations in trading price histories so as to only consider the occurrence of greater movements, effectively eliminating the "noise."

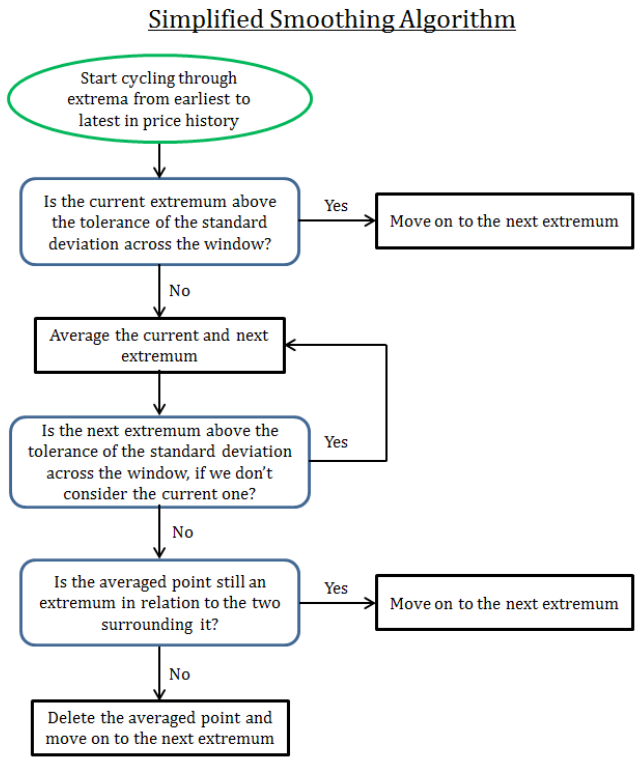
Similarities appear in the smoothing algorithm development of previous studies after Lo, Mamaysky, and Wang (2000) made popular the use of a kernel regression estimator used to smooth the raw trading data. In fact, Savin, Weller, and Zvingelis (2007) and Dawson and Steeley (2003) use the same kernel regression smoothing function. Lo, Mamaysky, and Wang (2000), however, note in their paper that a technique that depends on smoothing alone for the identification of extrema is a risk-inherent approach, as finding the correct balance between over- and under-smoothing is extremely difficult, and thus a gamble of finding correct formations in the smoothed data that accurately represent the raw trading price data.

Therefore, our process, a combination of a local regression using weighted linear least squares (locally weighted scatterplot smoothing—LOESS) and an algorithm for eliminating insignificant extrema, was created as a response to that call to devise a more rigorous approach to finding extrema that are "visually significant"; this is a key distinction needed to lead to the automation of pattern recognition by attempting to bridge the gap between the scientific and artistic portions of charting pattern identification. Correspondingly, the methodology of our project uses a small level of initial smoothing and then employs an algorithm that systematically eliminates some of the remaining extrema in the smoothed data that would not be considered significant compared to some target formation length. We wrote the pattern recognition code for both the head-and-shoulders and inverse head-and-shoulders formations through MATLAB.

Our initial smoothing function is similar to the kernel regressions used by the previous studies in that it creates an average for each point of the time-series data that depends on some weighted consideration of the surrounding points. Specifically, the weight of the smoothing functions used in previous studies, as well as in our work, places more emphasis on the points directly surrounding a given point and less emphasis on those further away. It is advantageous to use a weighted (and, for our study, more significantly localized than previous studies) approach to ensure no over-smoothing occurs. The LOESS function and the kernel regression differ simply in that the LOESS uses a quadratic polynomial regression while the kernel uses a probability distribution function of surrounding points. LOESS depends on one parameter: the percentage of the total data surrounding a given point that is used in the regression. The higher the value of this parameter, the more the dataset will be smoothed. Manipulating this parameter, therefore, allows us to target formations of differing lengths. We refer to this parameter in our smoothing algorithm as the "smoothing level."

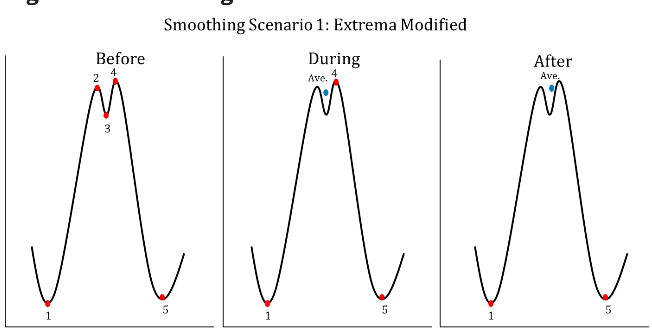
Once the data has been smoothed using the LOESS function, our process identifies each of the potential relative extrema. For the price of the commodity expressed as P_i, where i is the i^{th} trading day, each potential relative maximum is defined as a point P_i, such that $P_i > max\,(P_{i-1},P_{i+1})$ and each potential relative minimum is defined as a point P_i, such that $P_i < min\,(P_{i-1},P_{i+1})$. With each potential relative extrema found after the LOESS smoothing, our algorithm then combs through the data an additional time to determine which of the potential relative extrema are frivolous (i.e., points that would not be considered visually significant by a chartist). This process utilizes two additional parameters: the "window," or number of days surrounding a potential relative extrema by which to calculate the standard deviation of the local data, and the "tolerance," or percentage of the standard deviation across the "window" that two sequential potential extrema must break to be considered significantly different. A violation of this tolerance leads to some sort of modification (either elimination or averaging) of the two sequential insignificant extrema. Specifically, using the tolerance and window parameters, the algorithm uses a series of tests for each potential relative extremum that can result in three actions: the current extremum is identified as significant and is left alone, the current extremum is identified as frivolous and is averaged with the surrounding extrema, or the current extremum is identified as frivolous and is eliminated. That series of tests is illustrated in Figure 5.

Figure 5. Series of Tests for Each Potential Relative Extremum



We designed this process to handle two generalized examples, displayed in Figures 6 and 7. In Figure 6, the smoothing algorithm would start with consideration of (1), the first potential extremum, and cycle sequentially through each point after completing the series of tests relevant for each point.

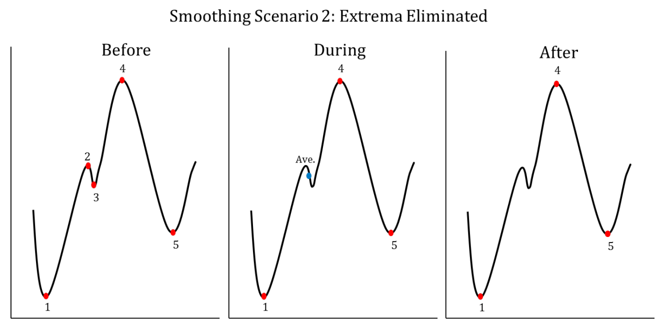
Figure 6. Smoothing Scenario 1



At (1), the algorithm would stop on the first step, after identifying that the difference in height between (1) and (2) is significantly greater than the tolerance level across the window. Moving on to (2), however, would not yield the same result, since the height differential between (2) and (3) does not meet the tolerance across the window. The algorithm would then average (2) and (3) and restart the steps, now considering the averaged point. The algorithm now identifies the new averaged point and (4) as failing to meet the tolerance level, so those two points are again averaged, and the algorithm now considers this newly averaged point. The height of (Ave) is significantly different from (1) and (5), so it will not be averaged further, but before moving on to consider (5), the algorithm checks to ensure that (Ave) is still a relative extremum in relation to (1) and (5). In this case, (Ave) is a relative maximum compared to (1) and (5), so it moves to consider (5). After the algorithm is finished with this section, it has identified (1), (Ave), and (5) as the visually significant extrema.

Figure 7 displays a slightly different situation. The algorithm again starts at (1) where, similarly to Figure 6, the point is identified as meeting the tolerance for height difference between (1) and (2).

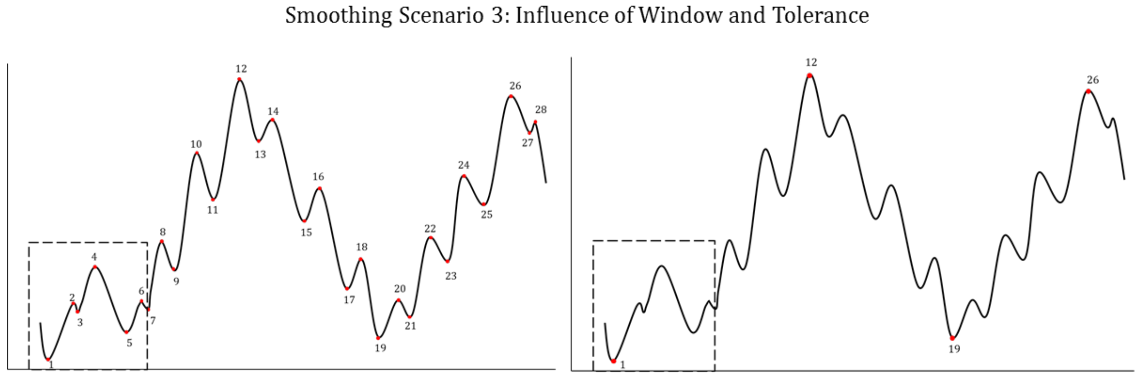
Figure 7. Smoothing Scenario 2



Again, (2) and (3) fail this test, so the two points are then averaged. Because the height of (Ave) is significantly different than those of (1) and (4), the algorithm again checks to see if it is still an extremum relative to the two surrounding it. The averaged point, in this example, is neither a relative maximum or minimum in relation to (1) and (4) and is therefore eliminated. After the smoothing algorithm is employed in this section, only (1), (4), and (5) remain, and these points are deemed, according to those parameters, as visually significant.

It is important to note that this result would only occur for some combination of the window and tolerance parameters. Under different parameters, it is possible that the height difference between (1), (Ave), and (5) in the last stage of Figure 7 would actually violate the tolerance rather than exceed it as in the given example, and thus the points would be averaged or eliminated instead of left as is. Consider the example in Figure 8, where we have the same price history section as in Figure 7 (in the dotted box), but in this case, the window is expanded to include additional data. Because the window has expanded, the standard deviation across that window has increased and, correspondingly, the tolerance has increased. In relation to this new window, the height difference between (4) and (5) is not large enough to break the tolerance, and the two are thus not identified by the algorithm as being visually significant. Indeed, after the algorithm is employed across this larger section, only (1), (12), (19), and (26) are considered to be significant extrema.

Figure 8. Smoothing Scenario 3



By having the computer loop through massive iterations of different combinations of the smoothing level, window, and tolerance parameters, we achieve different recognitions of “visually significant” extrema in order to find formations of differing sizes and differing scales; we argue this is the same process that a chartist would use, almost subconsciously, as she was looking for a formation of 60—90 days rather than 0—30 days long. At each stage of the loop, we first check to see if any five sequential extrema in the list of significant extrema identified by the specified smoothing level, window, and tolerance of a given trial meet the requirements of a head-and-shoulders or inverse head-and-shoulders formation.

Parameterization and Error Calculations

To find head-and-shoulders and inverse head-and-shoulders formations in the list of significant extrema, we parameterized the formations using terminology that the computer can recognize. We developed these parameters, or requirements, based on those used by Lo, Mamaysky, and Wang (2000) and Savin, Weller, and Zvingelis (2007). The head-and-shoulders formation is defined as five sequential extrema, E_1, E_2, E_3, E_4, and E_5, that meet the following specifications:

- E_1, E_3, and E_5 are relative maxima (head, left, and right shoulders)
- E_2 and E_4 are relative minima (both neck points)
- $E_3 > (E_1, E_5)$ (head is taller than left and right shoulders)
- $E_1 > E_2$ (left shoulder is taller than left neck point)
- $E_5 > E_4$ (right shoulder is taller than right neck point)
- $|E_2 - E_4| < 0.04 \times \frac{E_2+E_4}{2}$ (neck points are relatively level, within a 4% tolerance)
- $|E_1 - E_5| < 0.04 \times \frac{E_1+E_5}{2}$ (shoulders are relatively level, within a 4% tolerance)

Similarly, the inverse head-and-shoulders formation is defined as five sequential extrema, E_1, E_2, E_3, E_4, and E_5, that meet the following specifications:

- E_1, E_3, and E_5 are relative minima (head, left, and right shoulders)
- E_2 and E_4 are relative maxima (both neck points)
- $E_3 < (E_1, E_5)$ (head is below left and right shoulders)
- $E_1 < E_2$ (left shoulder is below left neck point)
- $E_5 < E_4$ (right shoulder is below right neck point)
- $|E_2 - E_4| < 0.04 \times \frac{E_2+E_4}{2}$ (neck points are relatively level, within a 4% tolerance)
- $|E_1 - E_5| < 0.04 \times \frac{E_1+E_5}{2}$ (shoulders are relatively level, within a 4% tolerance)

Additionally, we ensure that a pattern recognized as a head-and-shoulders formation occurs after an up-trend, and an inverse head-and-shoulders formation occurs after a down-trend. The process for trend analysis is discussed in the next section.

The parameterizations of Lo, Mamaysky, and Wang (2000) and Savin, Weller, and Zvingelis (2007) differ slightly, in that Lo, Mamaysky, and Wang (2000) include a lower tolerance level within which the neck points and shoulders must fall (1.5% rather than 4%), while Savin, Weller, and Zvingelis (2007) add four additional restrictions, providing proportion deviation limits for the five points. For both Lo, Mamaysky, and Wang (2000) and Savin, Weller, and Zvingelis (2007), the sets of five sequential extrema that met their respective requirements are designated as the actual head-and-shoulders or inverse head-and-shoulders patterns contained within the security of interest's price history. For our study, we took a different approach, using the broadest elements of these two parameterizations, choosing the lower tolerance level of Savin, Weller, and Zvingelis (2007) while also not including the same proportionality requirements. Rather, we developed proportions of what would be considered the “ideal” formation, and instead of considering *every* formation that meets the general requirements of a true formation, we consider them potential formations and quantify how “good” each of the formations is. Specifically, looking at the set of five extrema that make up a potential formation (identified after meeting the requirements listed above), we compare each potential formation's proportions to the ideal proportions, calculating an error term based on the difference between the two. In this way, we can determine the point at which an identified formation is no longer visually consistent with what a chartist would consider to be a pattern, as well as add another contribution of this study by exploring the predictive capabilities of different kinds of formations (i.e., those that are of differing levels of closeness of fit to the ideal), with the assumption that formations whose proportions are closer to the ideal will have better trend reversal predictive accuracy than those with higher error terms.

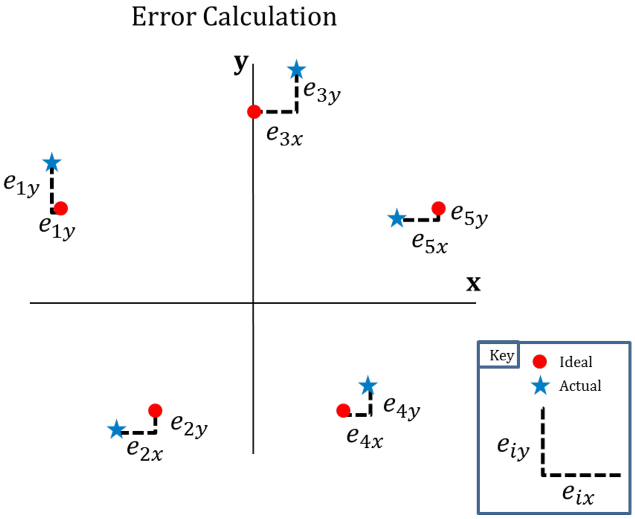
Using the work done by Osler and Chang (1995), we defined the ideal proportions of head-and-shoulders and inverse head-and-shoulders formations relative to the *x*-scale and *y*-scale, defined as the change in days between the left and right shoulders and the change in price between the head and average of the two neck points, respectively. The proportions of the ideal head-and-shoulders formation, displayed in Figure 9, are such that the difference between the *x*-values, or days, of each extrema is 1/4 of the *x*-scale; the difference between the y-values, or price, of the head and two shoulders is 1/3 of the *y*-scale; and the difference between the *y*-values of the two shoulders and the two neck points is 2/3 of the *y*-scale. These proportions are easily translated to the ideal inverse head-and-shoulders formation.

With the ideal proportions scaled to a set of five actual extrema that were identified as a potential formation, we calculate the mean squared percent error (MSPE) between the five actual and ideal points by $MSPE = \sum_{i=1}^{5}(e_{ix} + e_{iy})^2$, where

- e_{ix} is the difference in *x*-value between E_i (actual extremum) and I_i (ideal extremum)
- e_{iy} is the difference in y-value between E_i (actual extremum) and I_i (ideal extremum)

This calculation is illustrated in Figure 10. After visually looking at the results of this error calculation in our original results, we concluded that a potential formation whose MSPE exceeded 0.8 was no longer visually consistent with a head-and-shoulders or inverse head-and-shoulders formation. Therefore, the potential formations that have MSPE greater than 0.8 are eliminated, and we consider the remaining formations actual, visually representative formations, to be included in our results.

Figure 10. Calculating the MSPE Between the Five Actual and Ideal Points

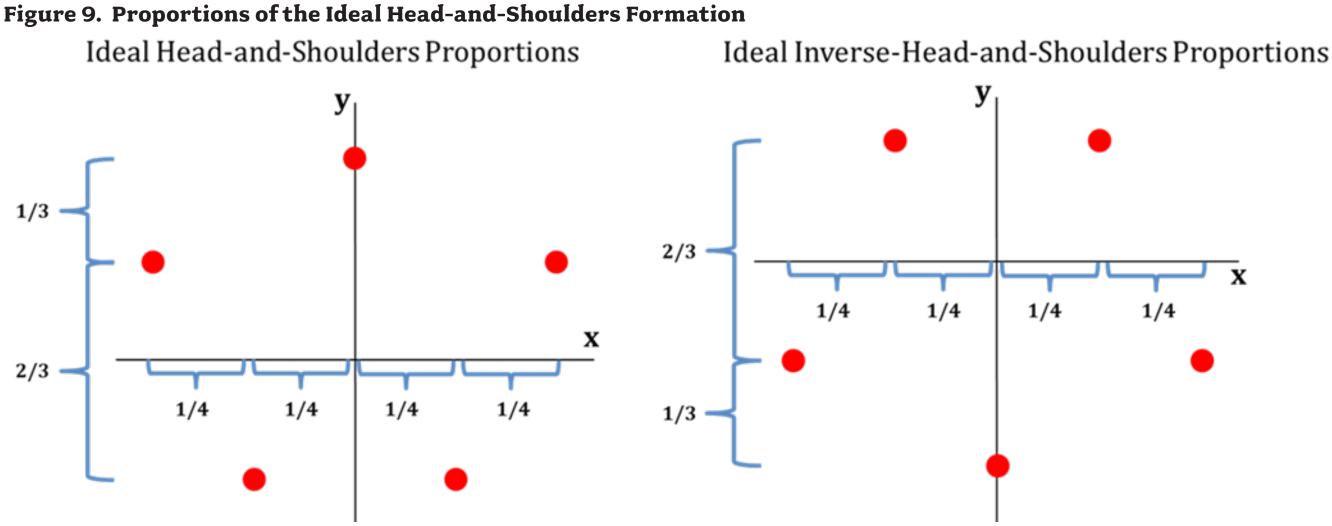


Trend Analysis

To determine whether or not a formation correctly predicted a trend reversal, we needed a process for identifying the trend lines both preceding and following a formation. Much like the recognition of charting patterns, drawing trend lines in a price history of a security is rather subjective, and again relies upon the chartist's judgment; in this case, though, the subjectivity is applied when determining the slope and length of the current trend. The question we need trend analysis to answer is, "Are the slopes of the back trend line and forward trend line opposite signs?" For example, "Is the slope of the back-trend prior to a head-and-shoulders positive (up-trend) and the slope of the forward-trend following a head-and-shoulders negative (down-trend)?" If so, the formation correctly predicted a trend reversal as intended. If not, the formation failed in its indication.

As in the process outlined by Kirkpatrick and Dahlquist (2011),

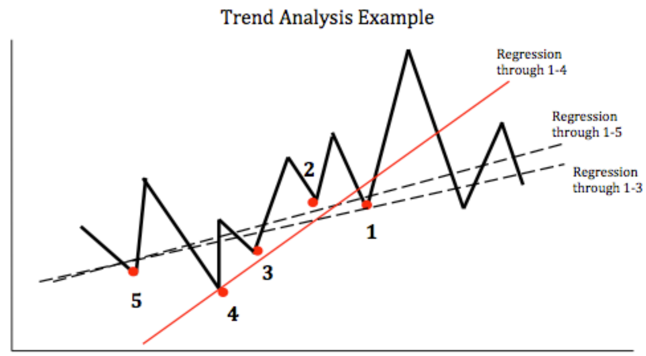
Figure 9. Proportions of the Ideal Head-and-Shoulders Formation



we used simple linear regressions to conduct trend analysis on the data immediately surrounding the series of extrema identified as actual head-and-shoulders or inverse head-and-shoulders formations. Linear regression is a statistical process that finds the best fitting line through a set of data. It produces two metrics that are of interest to trend analysis of a commodity's price history; first, the slope of the best-fit line, which translates to the intensity of the current trend and whether or not it is an up (positive slope) or down (negative slope) trend. Second, the R^2 value, which quantifies how well the actual data run through the regression line of best fit, which translates to how well defined the price trend is.

Trend lines in a traded security's price history are typically drawn through the relative minima for an up-trend and the relative maxima for a down-trend, and they are not set in length in comparison to the length of a charting pattern. Instead, they may be relatively long or short—another metric by which to say a trend is "strong" or well-defined. Thus, in an effort to avoid restricting the length of a potential trend line relative to the formation length (e.g., running a linear regression on all relative minima that occur for 60 days prior to a 30-day-long head-and-shoulders formation), we took a dynamic approach to automating the linear regression process. We define a window, twice the length of the specific formation of interest, across which to run linear regressions on series of relative extrema. For example, in the case of investigating the up-trend prior to a head-and-shoulders formation, we begin by running a linear regression on the three relative minima that occur before the left neck point, and continue running additional regressions while adding one immediately preceding minima to the series, until we stop on the last relative minima within the set window. Now, with an assortment of possible trend lines created by the dynamic linear regressions, we choose the trend line that maximizes the R^2 value, or metric of best fit, with preference for longer trends. The process is roughly depicted in Figure 11, where the solid red line is identified as the trend line that maximizes the R^2. The process for investigating forward trends is similar but instead, sequentially adds one additional extrema moving forward in time rather than backwards.

Figure 11. Trend Analysis



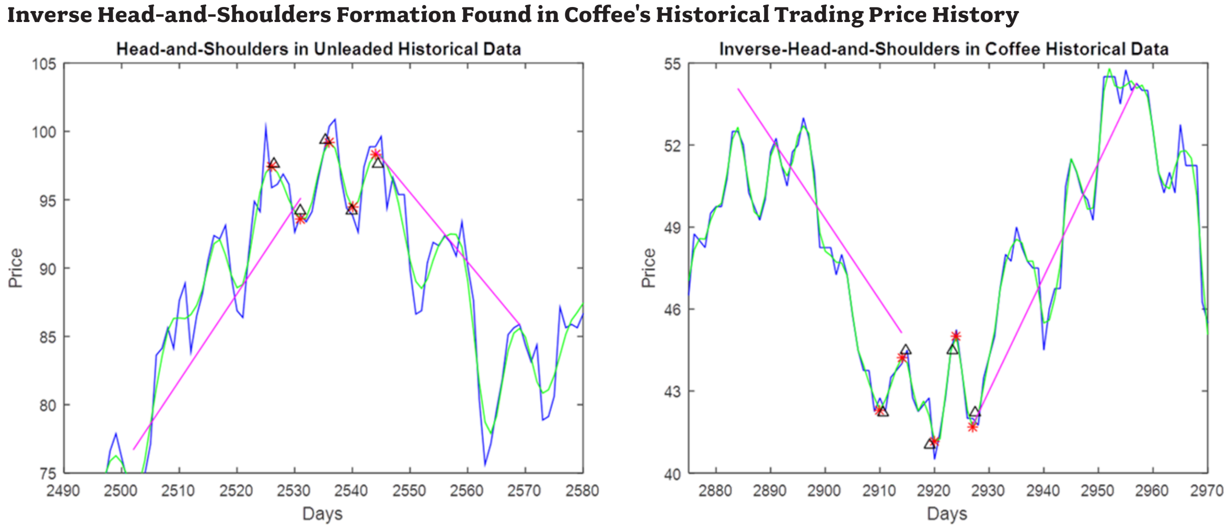
Now, with the means by which to have a computer identify not only the locations of charting patterns in a commodity's price history, but also whether or not the pattern at each location was successful in predicting a trend reversal, we can explore the overall predictive capabilities of the formations as well as what specific aspects of each pattern influence its performance.

Results

MATLAB Function Outputs

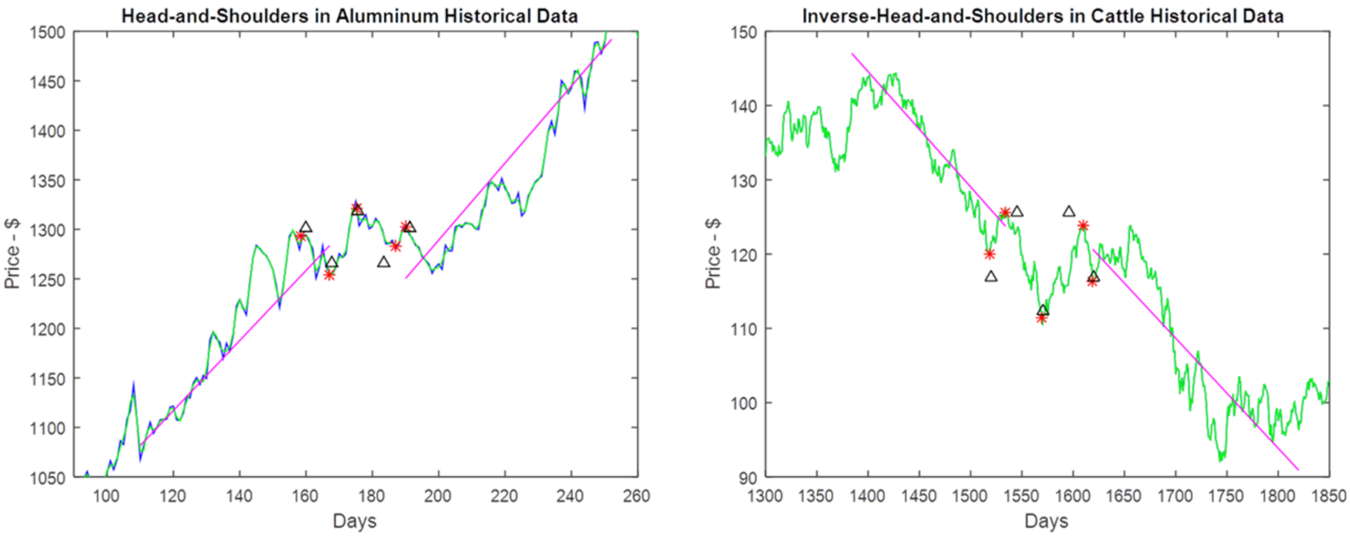
Figure 12 displays two examples of formations that were identified by our MATLAB functions. On the left is a head-and-shoulders formation found in unleaded gasoline's historical trading price history, and on the right, an inverse head-and-shoulders formation found in coffee's historical trading price history. In these output figures, the raw trading data are designated by the blue lines; the smoothed data (that resulted from our smoothing function) are designated by the green lines; the actual formation extrema (identified by our smoothing algorithm and the parameterization for each formation) are designated by red stars; the five ideal formation extrema (scaled from the ideal proportions) are designated by the black triangles; and finally, both the back and forward trend lines are designated by the pink lines. In each of these two instances, the formations were correct in predicting trend reversals.

Figure 12. Left: Head-and-Shoulders Formation Found in Unleaded Gasoline's Historical Trading Price History; Right: Inverse Head-and-Shoulders Formation Found in Coffee's Historical Trading Price History



As was expected, however, not every identified formation in the data was successful in predicting a trend reversal. Figure 13 displays two instances (a head-and-shoulders formation in aluminum's price history and an inverse head-and-shoulders in cattle's price history) in which the slope of the trend following the formation remains the same as that of the back trend, and thus no reversal occurred.

Figure 13. Left: Head-and-Shoulders Formation in Aluminum's Price History; Right: Inverse Head-and-Shoulders in Cattle's Price History



With a large dataset to analyze and a significant number of identified formations, we decided to create a Graphical User Interface (GUI) within MATLAB to act as a command center by which to control our functions and organize our results. Through this GUI, we can designate which type of pattern we want to search for, the commodity within which we want to search for instances of that pattern, and the ranges of the smoothing parameters for the functions to loop through. Therefore, by using this GUI after we fine-tuned each of our pattern-recognition functions, there was no need to interact with the coding any further, as we moved on to our data collection and analysis phases. The GUI also gives the ability to include a human in the pattern recognition process. The GUI user may review each formation identified by the functions and have a final say as to whether or not each identified formation is visually representative of a pattern. While this functionality was beneficial to us when fine-tuning our functions and also helps ensure that the user has an added level of confidence in the integrity of the output results, it is not necessary to complete the pattern recognition process and thus, does not impede on the automated nature of the identification.

After completing the data collection on all 17 commodities, we found 308 head-and-shoulders and 293 inverse head-and-shoulders formations contained within the price histories. The head-and-shoulders formations correctly predicted a reversal from an up-trend to a down-trend in 57% of identified locations, while the inverse head-and-shoulders correctly predicted a reversal from a down-trend to an up-trend in 63% of identified locations.

These results are supported by previous studies. Lo, Mamaysky, and Wang (2000) found, after conducting their automated pattern recognition, that roughly 60% of formations correctly predicted a trend reversal. While investors would hope to be able to have a higher degree of predictive accuracy than 60%, a success rate greater than 50% implies that, if properly implemented in a trading strategy over time, an investor can make a profit when selling a given commodity directly after a head-and-shoulders formation and buying a given commodity directly after an inverse head-and-shoulders formation. However, many trend reversals occur without the presence of a head-and-shoulders or inverse head-and-shoulders formation; the presence of either of these two formations is merely an indication of a reversal, not every reversal. Therefore, trading strategies utilizing these formations for buy and sell signals would still need to account for those situations. Additionally, we have merely identified the success at picking a reversal of a trend; we did not calculate profits associated with any systematic trading. Thus, a success rate of 60% does not necessarily equate to cumulative positive returns, especially after inclusion of transaction costs.

Statistical Analysis

To further explore the qualities of each formation that lead to its predictive performance, we conducted several statistical tests on our results. Specifically, we used Rank-Sum hypothesis tests that would look for a statistically significant difference between the means, or averages, of the MSPE; the relative length of the back trend lines, calculated by the length of the trend divided by the length of the formation; and the formation length of successful versus unsuccessful formations. If each hypothesis test rejects the null-hypothesis (that there is no significant difference in means between the successful and unsuccessful formations for a given metric), then we may conclude that the given metric does, in fact, have an impact on the pattern's predictive capabilities.

We chose to test these three particular metrics based on our intuitive assumptions of what their impact may be.

Perhaps formations that have lower MSPE (i.e., they are closer in proportions to what a chartist would consider the ideal formation) have a better chance of accurately predicting trend reversal. Similarly, perhaps for formations that occur following a trend line that is relatively long compared to its own length, the violation of the well-defined trend would lead to better predictive success rates. Finally, it is possible there is an innate level of variation within the trading price volatility of a commodity that would lead formations of certain lengths to better predict the movement of that commodity. Below, Tables 1, 2, and 3 contain the breakdowns of the three metrics across each type of pattern.

Table 1. MSPE vs. Success Rate

Head-and-Shoulders				Inverse Head-and-Shoulders			
Length	# Formations	# Passed	% Passed	Length	# Formations	# Passed	% Passed
0–0.5	56	33	59%	0–0.5	50	33	66%
0.5–0.6	70	39	56%	0.5–0.6	64	38	59%
0.6–0.7	77	42	55%	0.6–0.7	70	41	59%
0.7+	105	63	60%	0.7+	109	66	61%
Total	308	177	57%	Total	293	178	61%

Table 2. Relative Back-Trend Line vs. Success Rate

Head-and-Shoulders				Inverse Head-and-Shoulders			
Length	# Formations	# Passed	% Passed	Length	# Formations	# Passed	% Passed
0–0.5	14	12	86%	0–0.5	10	6	60%
0.5–1.0	49	28	57%	0.5–1.0	68	38	56%
1.0–1.5	79	45	57%	1.0–1.5	94	59	63%
1.5–2.0	166	92	55%	1.5–2.0	121	75	62%
Total	308	177	57%	Total	293	178	61%

Table 3. Formation Length vs. Success Rate

Head-and-Shoulders				Inverse Head-and-Shoulders			
Length (days)	# Formations	# Passed	% Passed	Length (days)	# Formations	# Passed	% Passed
0–30	174	105	60%	0–30	162	87	54%
31–60	73	35	48%	31–60	72	52	72%
61–90	30	21	70%	61–90	26	20	77%
90+	31	16	52%	90+	33	19	58%
Total	308	177	57%	Total	293	178	61%

Table 4 presents results for the Rank-Sum tests on MSPE, relative back-trend length, and formation length, both for the head-and-shoulders and inverse head-and-shoulders formations. The P-values are well above the 0.05 tolerance level; thus, we failed to reject the null-hypothesis that there is no significant difference in means for these metrics between successful and unsuccessful formations. That is to say, we conclude that none of the metrics have a significant impact on the predictive capabilities of the patterns.

Table 4. Rank Sum Tests P-Values

Metric	Head-and-Shoulders	Inverse Head-and-Shoulders
MSPE	0.5894	0.6817
Back-Trend Length	0.6684	0.6397
Form Length	0.9572	0.2233

While for the relative back-trend length and formation length, this lack of a relationship is not necessarily too puzzling, it is unusual that MSPE does not seem to have an impact on the predictive capabilities of the formations. It seems very logical that formations closer to the ideal proportions for which a chartist would look should perform better than those that are relatively crooked or misshaped. To make sense of this finding, we must consider the subjective nature of charting pattern recognition. We suspect that established traders are attempting to find the pattern that approximates the head-and-shoulders, or its counterpart, such that an ideally shaped pattern would only be of help to the novice technical investor. We would expect novice chartists to "hone their craft" using paper trades, versus actual trades, only feeling confident enough to risk actual capital once they have demonstrated an ability to successfully identify even approximate patterns. If this is true, then there is no need for a head-and-shoulders or inverse head-and-shoulders formation to have perfect proportions but rather, as long as a specific pattern is proportionate enough that it is visually representative of a formation in the eyes of a chartist, it will have predictive success to some degree. Exploration of different quantifications of how "ideal" or "good" an identified formation is would be beneficial in further exploring this finding.

Conclusion

This project attempted to address the lack of an efficient means to identify occurrences of patterns within traded securities' price histories that are, in practical applications, currently entirely reliant upon visual inspection. The time-consuming nature of this reliance on visual inspection has made it difficult to determine the true success rates of those patterns' indications of trend reversal, and thus, confidence in their successful implementation in trading strategies is limited. As a response, we created a means by which a computer can analyze past trading data, identify head-and-shoulders and inverse head-and-shoulders patterns, and assess the predictive accuracy within that data at speeds that are nonreplicable by a human. Even with the 400 combinations of smoothing parameters that we looped through, the computer analyzed 25 years of commodity data in approximately 20 minutes.

Additionally, we ensured throughout the development of our functions within MATLAB, that the automated pattern recognition process is entirely dynamic (i.e., the functions are not limited to analysis of the price histories of the 17 commodities that we studied in this project). Rather, the functions are capable of recognizing patterns in any time-series data. Therefore, the reach of this project is not limited to our findings of roughly 60% predictive accuracy of head-and-shoulders and inverse-head-and-shoulders formations in the price histories of the 17 formations on which we conducted our analysis. Instead, the real takeaway of this project is a sustainable tool, housed within the GUI in MATLAB, which may be used by any individual interested in looking for and assessing the success rates of head-and-shoulders and inverse head-and-shoulders formations in any security's price history. This opens the door for further academic study of these, or other patterns, in additional commodities, other securities (such as common stock and currency exchange rates), or even nonfinancial-related time series data. We also see this as a tool that can provide value for the trader, not necessarily as a real-time trading tool but as a tool to perform quantitative analysis to help them calibrate their technical trading strategies, when these strategies include charting patterns.

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Notes

1 We consider the study of charts to forecast changes in the price trend as a subspecialty within the more broadly defined specialty of technical analysis, which may use chart patterns in conjunction with more quantitative analytical techniques, such as moving averages, or other indicators deemed relevant.

2 The list of commodities includes corn, wheat, sugar, soybeans, coffee, livestock, hogs, cattle, gold, silver, platinum, aluminum, copper, WTI, brent, natural gas, and unleaded gas.

On the Great Dow Theory

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Abstract

Charles H. Dow was the first-ever person to have correctly described the stock market functions, correctly captured the mechanism of the stock market pricing, precisely described the rules of the movement of the stock market, and put into place the stock market barometer in the financial history of the world.

The Dow Theory is not Voodoo finance. Rather, the Dow Theory is the stock market theory with rich scientific content being confronted with temporary prejudices and sheer folly. The Dow Theory is not, as generally taken for granted by many people, just a simple technical analysis theory. In fact, the Dow Theory is a comprehensive system of scientific thoughts on the stock market encompassing the stock market functions, the mechanism of the stock market pricing, the stock price behavior, and the scientific investment strategy, along with other significant issues related to the stock market.

Introduction

Nothing is more certain that the market has three well defined movements which fit into each other. The first is the daily variation due to local causes and the balance of buying or selling at that particular time. The secondary movement covers a period ranging from ten days to sixty days, averaging probably between thirty to forty days. The third swing is the great move covering from four to six years.

-Charles H. Dow

The purpose of this research paper[1] is to bring to the attention of the financial academic circles, the financial investment management circles, and the technical analysis industry the latest research results on the Dow Theory. At the same time, it is the author's intention to appeal to financial academic circles, the financial investment management circles, and the technical analysis industry to reevaluate the scientific connotations of the Dow Theory.

Charles H. Dow was the founder of the Dow-Jones Financial News Service in New York and founder and first editor of *The Wall Street Journal.* He died prematurely in December 1902, at the age of 52. While living, Charles H. Dow had not published his thoughts on the stock market in the form of a book. Instead, he had published them in the format of editorials in *The Wall Street Journal.* After Charles H. Dow passed away, William Peter Hamilton succeeded him as the chief editor of *The Wall Street Journal.* William Peter Hamilton had distinguished himself in carrying forward his predecessor's thoughts on the stock market with his unusual wisdom and intelligence in collating Dow's thoughts on the stock market behavior in a book entitled *The Stock Market Barometer,* which has since become the most authoritative writing on the Dow Theory,[2] and the book has also been generally acknowledged as the foundation stone of the traditional technical analysis theory.

The present paper targets the aforementioned *The Stock Market Barometer* as its object of research.[3] The paper divides the Dow Theory into three parts, viz. the scientific thoughts of the Dow Theory on the stock market (macro portion), the assertion of the Dow Theory concerning the stock price behavior (micro portion), and the great brain-child by Charles H. Dow—the Stock Market Barometer. Due to lack of space, this paper lays emphasis on only two portions: namely, the scientific thoughts of the Dow Theory on the stock market and the great invention by Charles H. Dow—the Stock Market Barometer. The paper only takes a brief look at the assertions of the Dow Theory concerning the stock price behavior. The conclusions of this paper show that, first of all, in spite of the dire lack of stock market data at the time, Charles H. Dow creatively set up DJIA and DJRA to predict and analyze the future ups and downs of economic activities down the road through the analysis of the common trends of these two stock indexes (as the barometer of the stock market). Like a demigod, he magically perceived the core of the capricious stock market in this way.

Second of all, Charles H. Dow was the first-ever person to have correctly described the stock market functions, correctly captured the mechanism of the stock market pricing, precisely described the rules of the movement of the stock market, and put into place the stock market barometer in the financial history of the world.

Thirdly, Charles H. Dow's assertions on the stock market behavior were made substantially at the same time when Louis Bachelier published his "Theory of Speculation" (1900). The Dow Theory regarding the thinking that the stock market behavior is knowable was published more than 14 years earlier than Keynes' assertion that the investor short-term expectation is knowable (in his famous writing).[4] The concepts of the stock value and discounting advanced by the Dow Theory were over 16 years earlier than similar assertions made by Williams in his "Theory of Investment Value" (1938). The Dow Theory's discourse on the stock market pricing was more than 40 years earlier than Sharpe's CAPM (1964). Moreover, the assertion by the Dow Theory that stock price reflects expeditiously the basic factors was about 50 years earlier than the famous discourse that the stock prices always "fully reflect" available information in Fama's Efficient Market Hypothesis (1970).

This paper is arranged in the following way: apart from the Introduction, the second section delves into the scientific thoughts on the stock market associated with the Dow Theory and provides brief but succinct comments on the assertions of the Dow Theory concerning the stock price behavior. A third section analyzes the great invention by Charles H. Dow—the stock market barometer. A fourth section briefly examines why the Dow Theory has not been carried forward and developed in a scientific manner. The final section provides concluding remarks on the present paper.

Scientific Thoughts of the Dow Theory on the Stock Market

The Dow Theory is not, as generally taken for granted by many people, just a simple technical analysis theory. It is in reality a system of scientific thoughts on the stock market encompassing the stock market functions, the mechanism of the stock market pricing, the stock price behavior, and scientific investment strategy, along with other important issues associated with the stock market.

Scientific thoughts of the Dow Theory on the stock market (macro portion)

The Dow Theory correctly describes the major functions of the stock market

(i) The Dow Theory correctly points out that the stock market is the barometer of the country's economy and that is none other than the major function of the stock market.

[Hamilton, page 40] writes: the stock market is the barometer of the country's, and even of the world's, business, and the theory shows how to read it.

(ii) The Dow Theory correctly describes the price discovery function of the stock market.

[Hamilton, page 40-42] writes: the sum and tendency of the transactions in the Stock Exchange represent the sum of all Wall Street 's knowledge of the past, immediate and remote, applied to the discounting of the future. There is no need to add to the averages as some statisticians do, elaborate compilations of commodity price index numbers, bank clearings, fluctuations in exchange, volume of domestic and foreign trade or anything else. Wall Street considers all these things. It properly regards them as experience of the past, if only of the immediate past, to be used for estimating the future.

In the price movements, as Dow correctly saw, the sum of every scrap of knowledge available to Wall Street is reflected as far ahead as the clearest vision in Wall Street can see. The market is not saying what the condition of business is today. It is saying what that condition will be months ahead. Even with manipulation, embracing not one but several leading stocks, the market is saying the same thing, and is bigger than the manipulation.

(iii) The Dow Theory correctly describes the function of the stock market pricing.

First, the Dow Theory correctly describes the pricing mechanism of the stock market.

[Hamilton, page 8] writes: the price movement represents the aggregate knowledge of Wall Street and, above all, its aggregated knowledge of coming events…; The market represents everything everybody knows, hopes, believes, anticipates.

[Hamilton, page 127] explains: the market movement reflects all the real knowledge available, and every day's trading sifts the wheat from the chaff. If the resultant showing of grain is poor, the market reflects the estimate of its value in lower prices. If the winnowing is good, prices advance long before the most industrious and up-to-date student of general business conditions can bushel up the residue and set it forth in his pictorial chart.

[Hamilton, page 182] further explains: it has been said before that the stock market represents, in a crystallized form, the aggregate of all American knows about its own business, and, incidentally, about the business of its neighbors. When a man finds his jobbing trade or his factory showing a surplus, he tends to invest that surplus in easily negotiable securities. If this improvement is general, it is all reflected and anticipated in the market, for he can buy in July and carry on ample margin what he knows he can pay for outright when he divides profits at the end of the year. He does not wait until the end of the year, because he realizes that the knowledge he possesses in July will by that time have become common property, and will have been discounted in the price.

Secondly, the Dow Theory correctly describes the pricing basis and pricing process of the stock market.

[Hamilton, page 88-90] writes: all adjustments of the prices of these stocks individually must primarily be based upon values. For all practical purposes the Stock Exchange is an open market, and the business of such a market is to adjust conflicting estimates to a common basis which is expressed in the price… The stock market does not make its adjustment in a day. But over a period…This is the business of the stock market. It has to consider both basic values and prospects…At the close of a major downward movement, a primary bear market, prices will have passed below the line of values…Conversely, a bull market starts with stocks much below their real values, certain to be helped in anticipation by the general improvement in the country's business which the stock markets foresee and discounts. In the long advance values will be gradually overtaken.

[Hamilton, page 92] explains: every scrap of intelligence and knowledge available, uninfluenced in any real degree by manipulation, has been brought to bear in the adjustment of the stock market prices. Reproduction value, real estate value, franchises, right of way, good will—everything else—have been brought into the free-market estimate in a way which no valuation committee appointed by Congress could ever attain… But the Stock Exchange price records the value from day to day, from month to month, from year to year, from bull market to bear market, from one of Jevons's cycle dates to another.

[Hamilton, page 99] eloquently argues: "in the long run values make prices".

The Dow Theory correctly outlines the rules of the movement of the stock market in terms of applicability and knowability

(i) The Dow Theory advocates that the price discovery function and the rules of movement are the common features inherent to the stock market and that such features will not vary with the passage of time.

[Hamilton, page 14–15] writes: the law that governs the movement of the stock market, formulated here, would be equally true of the London Stock Exchange, the Paris Bourse or even the Berlin Bourse...The principles underlying that law would be true if those Stock Exchanges and ours were wiped out of existence. They would come into operation again, automatically and inevitably, with the re-establishment of a free market in securities in any great capital...But the stock market there would have the same quality of forecast which the New York market has if similar data were available...It would be possible to compile from the London Stock Exchange list two or more representative groups of stocks and show their primary, their secondary and their daily movements over the period of years...An average made up of the prices of the British railroads might well confirm our own.

(ii) The Dow Theory advocates that the movement of the stock market has its inherent rules and that such rules are knowable.

[Hamilton, page 58–59] writes: Order is Heaven's first law

If Wall Street is the general reservoir for the collection of the country's tiny streams of liquid capital, it is the clearinghouse for all the tiny contributions to the sum of facts of business. It cannot be too often repeated that the stock market movement represents the deductions from the accumulation of that truth, including the facts on building and real estate, bank clearings, business failures, money conditions, foreign trade, god movements, commodity prices, investment markets, crop conditions, railroad conditions, political factors and social conditions, but all of these with an almost limitless number of other things, each having its tiny trickle of stock market effect.

There must be laws governing these things, and it is our present purpose to see if we cannot formulate them usefully... But we shall all recognize that order is Heaven's first law, and that organized society, in the Stock Exchange or elsewhere, will tend to obey that law even if the unaided individual intelligence is not great enough to grasp it.

The Dow Theory scientifically points out that the investor should base their understanding of the stock price behavior on the stock value and market expectations together and take their investment decisions accordingly.

[Hamilton, page 75] writes: but it is a vital mistake to suppose that speculation in stocks (for the rise at least) is a sort of gamble in which no one can win unless there is an equivalent loss somebody else. There need be no such loss in a bull market.

[Hamilton, page 38] writes: the best way of reading the market is to read from the standpoint of values. The market is not like a balloon plunging hither and thither in the wind. As a whole, it represents a serious, well-considered effect on the part of far-sighted and well-informed men to adjust prices to such values as exist or which are expected to exist in the not too remote future..."In reading the market, therefore, the main point is to discover what a stock can be expected to be worth three months hence and then to see whether manipulators or investors are advancing the price of that stock toward those figures. It is often possible to read movements in the market very clearly in this way. To know value is to comprehend the meaning of movements in the market".

The assertions of the Dow Theory on the stock price behavior (micro portion)

The Dow Theory precisely describes the patterns of the movement in the stock market.

Movement in the stock market can be divided into three kinds of movement: namely, primary movement, secondary movement and daily variation.

According to [Hamilton, page 4–6], Dow's theory is fundamentally simple. He showed that there are, simultaneously, three movements in progress in the stock market. The major is the primary movement...It will be shown that this primary movement tends to run over a period of at least a year and is generally much longer. Coincident with it, or in the course of it, is Dow's secondary movement, represented by sharp rallies in a primary bear market and sharp reactions in a primary bull market...Concurrently with the primary and secondary movement of the market, and constant throughout, there obviously was, as Dow pointed out, the underlying fluctuation from day to day.

[Hamilton, page 23] writes: he was almost too cautious to come out with a flat dogmatic statement of his theory, however sound it was and however close and clear his reasoning might be...in the Review and Outlook of the *Wall Street Journal* of January 4, 1902, he says: "Nothing is more certain that the market has three well defined movements which fit into each other. The first is the daily variation due to local causes and the balance of buying or selling at that particular time. The secondary movement covers a period ranging from ten days to sixty days, averaging probably between thirty to forty days. The third swing is the great move covering from four to six years.

[Hamilton, page 23–24] comments: remember that Dow wrote this twenty years ago, and that he had not the records for analysis of the market movement which are now available. The extent of the primary movement, as given in this quotation, is proved to be far too long by subsequent experience; and a careful examination has shown me that the major swing before Dow wrote was never "from four to six years," rarely three years and oftener less than two. But Dow always had a reason for what he said, and his intellectual honestly assures those who knew him that it was at least an arguable reason.

The Dow Theory accurately points out the long-term upward trend of the stock market, and that such upward trend is not equal to the downward trend of the stock market.

[Hamilton, page 147] writes: so true is it that Wall Street is normally and healthily bullish...When we studied the major swings we saw that bull markets last longer than bear markets, and we might have seen that over a period of years long enough to average both bull and bear swings the tendency seems upward, or at least has heretofore advanced, with the growing wealth of the country.

[Hamilton, page 123] writes: among the many things which our stock market averages prove, one stands out clearly. It is that so far as the price movement is concerned action and reaction are not equal. We do not have an instance of a bull market offsets in the extent of its advance by an exactly corresponding decline in a bear market...We have seen that bull markets are, as a rule, of materially longer duration than bear markets. There is no automatically balancing equation there. I do not believe there is such an equation in human affairs anywhere.

The Dow Theory succinctly represents the bull market and bear market.

[Hamilton, page 32] writes: "It is a bull period as long as the average of one high point exceeds that of previous high points. It is a bear period when the low point becomes lower than the previous low points."

The Dow Theory correctly describes the relationship between the trading volume and the trend of the stock price movement. [Hamilton, page 136] explains that: it is worthwhile to note here that the volume of trading is always larger in a bull market than in a bear market. It expands as prices go up and contracts as they decline.

Future generations have summed up the Dow Theory viewpoints in one single sentence, viz. "Volume Goes with the Trend".

The Dow Theory accurately points out the absolute importance of the closing price to any analysis of the stock price behavior. This is what later generations have summed up in "Only Closing Prices Used". In the appendix, [Hamilton, page 288] points out, the averages are compiled from closing prices. In case there is no sale of a particular stock, the last previous close in used.

Charles H. Dow's Great Creation—The Stock Market Barometer

Charles H. Dow's intention in establishing the stock market barometer

[Hamilton, pages 2–4] writes: there seems to be a circle of panics and of times of prosperity. Anyone with a working knowledge of modern history could recite our panic dates—1837, 1857, 1866 (Overend-Gurney panic in London), 1873, 1884, 1893, 1907...What we need are soulless barometers, price indexes and averages to tell us where we are going and what we may expect.

[Hamilton, page 127] writes: few of us can be Keplers or Newtons, but it is possible to formulate working rules which will help and protect any man in that forecast of the future which he must necessarily make every day of his life. This is what the stock market barometer does. It makes no false claims. It admits highly human and obvious limitations. But such as it is, it can honestly claim that it has a quality of forecast which no other business record yet devised has even closely approached.

[Hamilton, page 45] writes: it will be shown at a later stage that throughout these market movements it was possible from the stock market barometer to predict, some valuable distance ahead, the development of the business of the country.

Logic and basis for Charles H. Dow in establishing the stock market barometer

First, the Dow Theory advocates that, in the free and competitive stock market wherein all stock shares are well distributed (instead of being monopolized or manipulated), the expectation of the future on the part of the investor, along with his/her profit-seeking behavior, will make the changes of the economy be reflected immediately into the stock prices. In this way, the stock market rapidly reflects the actual situation of the economy, leading to the conclusion that the stock market is the country's barometer. The pricing pattern and pricing mechanism of the stock market make it possible for the stock market to have the unique function to predict the immediate future.

Secondly, rules of the movements of the stock market are knowable. The three patterns of the movement of the stock market advocated by the Dow Theory are cases in point. Specifically, the Dow Theory advocates that the primary trend of the stock market can never be manipulated.

Lastly, the stock prices of different sectors in the stock market display a trend of movement in the same direction. Through the selection of trends reflective of changes of the stock indexes associated with several key representative sectors of the national economy, it is possible to predict trends in changes of the whole country's economy—which has effectively become a mere technicality.

The above is where the logic and key basis lie, insofar as the design of the barometer by Charles H. Dow is concerned. Based on the above three points, we can easily identify the following: 1) through analysis of the movement of the stock market, we are fully capable of predicting and judging ups and downs associated with economic activities; and 2) the Dow Theory represents an ideal instrument in deciphering the stock market barometer. Undoubtedly, the stock market barometer has been the brain-child and creation of a genuine genius!

The two averages must confirm

No one would negate the inherent scientific nature of the thoughts conceived by Charles H. Dow. Through analysis of the behavior of the stock indexes associated with several key representative sectors of the national economy, we are able to predict and analyze the ups and downs associated with economic activities. How then is it possible to enable the stock market barometer to accurately predict the trend of the economic movement? The Dow Theory provides an answer to this particular question: through the establishment of DJIA and DJRA, and analyzing their common movement trends with a view to predicting and analyzing success or failure of the involved economic activities. The Dow Theory lays repeated emphasis on the following key point: the two averages must confirm.

[Hamilton, pages 139–140] writes, this illustration serves to emphasize the fact that while the two averages may vary in strength they will not materially vary in direction, especially in a major movement. Throughout all the years in which both averages have been kept this rule has proved entirely dependable. It is not only true of the major swings of the market, but it is approximately true of the secondary reactions and rallies. It would not be true of the daily fluctuation, and it might be utterly misleading so far as individual stocks are concerned.

[Hamilton, page 185] comments, our two averages of railroad and industrial stocks must confirm each other to give weight at any inference drawn from the price movement. The history of the stock markets are shown by these averages, going back many years, and proves conclusively that the two averages move together.

The Dow Theory represents the functions of the stock market barometer in the following way

[Hamilton, page 97] writes: the stock market barometer shows present and prospective values. It is necessary in reading it to judge whether a long movement has carried the average prices below that line or above it.

[Hamilton, page 157] comments: we have seen that the stock market barometer does predict. It shows us what will happen to the general volume of business many months ahead. It even goes further and warns us of the danger of international events which could upset all ordinary calculations based on the course of business as inferred from the records.

[Hamilton, pages 263–264] further comments: it cannot too often be said that Dow's theory of the stock market movement is not a "system" for beating the market—a get-rich-quick scheme which converts the Wall Street district into a sort of Tom Tiddler's ground, where any man with a few dollars for margin can pick up gold and silver...But if he has learned what the market movement means and appreciates the opportunity given to him in the dullness after a typical reaction in a bull market, he stands more than an even chance of making a profit.

Charles H. Dow had a profound understanding of the absolute importance of the stock market that is free, competitive, and unmanipulated to the proper operation of his stock market barometer. At the same time, Charles H. Dow had voiced his concerns about government intervention in stock market behavior from the outset.

[Hamilton, page 73] writes: it has been shown that, for all practical purposes, manipulation has, and can have, no real effect in the main or primary movement of the stock market, as reflected in the averages. In a primary bull or bear market the actuating forces are above and beyond manipulation. But in the other movements of Dow's Theory, a secondary reaction in a bull market or the corresponding secondary rally in a bear market, or in the third movement (the daily fluctuation) which goes on all the time, there is room for manipulation, but only in individual stocks,

[Hamilton, page 218] comments: if there is one lesson which should have been burned in upon the public mind in the past decade, it is that when government interferes with private enterprise, even where that enterprise is directed to the development of a public utility, it can do incalculable harm and very little good.

The present-day stock market has experienced significant changes compared with the stock market at the time when the Dow Theory was unveiled. Impact being exerted on the stock market by the financial and hi-tech sectors has already become more prevalent than the traditional industrial and transportation sectors, with the Fed having become one of the major factors of the current stock market pricing. The primary trend of the stock market being unmanipulated assumed by the Dow Theory no longer stands in today's stock market environment. With the function of the stock market barometer being tampered with, changes in today's stock market do not necessarily reflect twists and turns of the national economy of a given country; what the stock market reflects could be the regulation and planning of the national economy on the part of the central bank or the government. The QE Policy promulgated by the Fed in 2009 and impacting the U.S. stock market over a eight-year time period provides a case in point.

Why the Dow Theory (Macro Portion) Could Not Be Carried Forward and Developed in a Scientific Way

Weakness of the Dow Theory

Although the Dow Theory has formulated systematic scientific thoughts on the stock market (macro portion) and rules describing the stock price behavior (micro portion), it has never been able to quantify, in a scientific manner, its scientific thoughts on the stock market. Nor has it ever been able to scientifically quantify its rules describing the stock price behavior. If we ever view the stock market behavior as a whole, the Dow Theory has only completed about 40% of the entire stock market research workload. The remaining 60% relating to the quantifying the scientific thoughts on the stock market and the formulation of the models describing the inner mechanism and rules of the stock market movement from the angle of microstructure of the stock market, and to further evolve and develop the Dow Theory (if needed) on the foregoing basis has been left to be accomplished by future generations.

Under the specific circumstances of the time, Charles H. Dow did not have access to the required stock market data for reference, and was not in a position to draw reference from any research papers on the stock market pricing. To make matters worse, he had not been able to refer to any research work on the stock price behavior. The Dow Theory's shortcomings in describing the stock price behavior are obvious. For instance, certain Dow Theory statements on the stock price behavior address only the symptoms rather than root cause of the issue. Even though some statements have turned out to be very accurate, the Dow Theory simply fails to tell us why they were so accurate in the first place. As the symptoms of the stock price behavior vary significantly, it is not at all surprising that investors would invariably experience difficulties and inadequacies with the Dow Theory in terms of operability over a short span of time.

Problem with effort to scientifically carry forward and develop the Dow Theory

Successors to William Peter Hamilton, such as Robert Rhea, Richard Schabacker, Robert D. Edwards, and John Magee, had come to understand the above constraints. They had, at different stages, changed the direction of research on the part of Charles H. Dow and William Peter Hamilton. Charles H. Dow's thinking on the stock market barometer had been expanded to formulate stock charts analysis of the behavior of individual stocks. In the wake of Robert D. Edwards and John Magee having systematically used stock charts to analyze stock indexes and individual stock prices, the systemized Dow Theory and stock charts analysis have jointly constituted the classical technical analysis theory.

If we perform a comparison between the Dow Theory described by Robert D. Edwards and John Magee with that of William Peter Hamilton, we can see that the Dow Theory, upon systemization by Robert D. Edwards and John Magee, has deleted the majority of contents dealing with the scientific thoughts (macro portion) on the stock market under the Dow Theory by William Peter Hamilton. In the current mainstream works of the technical analysis related to the Dow Theory, we are no longer able to find scientific thoughts on the stock market by William Peter Hamilton in his version of the Dow Theory.[5] A sad fact is: the majority of the scientific thoughts (macro portion) on the stock market associated with the Dow Theory have not been carried forward and developed.

To scientifically carry forward and develop the Dow Theory written by William Peter Hamilton, one of the conditions precedent is that we must be able to scientifically comprehend and validate the Dow Theory. However, the sad reality is that, even today, over 100 years after Charles H. Dow passed away, the contemporary standard financial investment theories still cannot meet this particular requirement.

Technical difficulties

First and foremost, the Dow Theory is directly bound up with the real investor behavior (such as expectation and evaluation). Such real investor behavior, in turn, is closely linked with the stock market behavior. They constitute the key components of our understanding of the stock market behaviour. Up to the present time, irrespective of the Wall Street or financial academic circles, it remains difficult to quantify the above real investor behaviour, and it has been difficult to quantify their relationship with the stock market behaviour.

Second of all, concepts espoused under the Dow Theory, such as trend and periodicity, are equally bound up with the real investor behavior. Due to difficulty in quantifying such real investor behavior, it is impossible for us to quantity these concepts describing such stock market behavior. In addition, Charles H. Dow had not provided readership with the logic and evidence lying behind the formulation of his thinking on the stock market behavior. As a result, to scientifically comprehend Charles H. Dow's thinking is no easy matter. Even William Peter Hamilton sometimes could only partially and incompletely understand the genius brains of Charles H. Dow. In fact, on certain judgments dealing with the stock price behaviour on the part of Charles H. Dow, William Peter Hamilton could have misunderstood Charles H. Dow.[6]

Inclement industrial environment

Although technical analysis and fundamental analysis were well received and extensively applied by the Wall Street, as from Cowles (1934),[7] testing of the Dow Theory providing strong evidence against the ability of Hamilton, the most famous Wall Street technician, to forecast the stock market, technical analysis has not been acceptable to the financial academic circles ever since. With the Efficient Market Theory becoming the cornerstone of the modern financial investment theories in the 1970s, technical analysis (including the Dow Theory) and the nature of the work performed by the technical analysts have been put under increasingly fierce attacks and reprimand. Not only has technical analysis been given the infamous name of "Voodoo Finance", but the entire technical analysis industry has been subjected to strong attacks. Such inclement environment created the situation whereby the entire technical analysis industry simply could not get adequate capable young talents to join in to undertake the basic research. Moreover, technical analysis theory (including the Dow Theory) could not be developed and carried forward in a healthy and scientific manner.

From the 1950s up to the present time, the total number of papers on technical analysis collectively published in the leading financial and economic journals are not as numerous as those carried by three issues of the *Journal of Finance* today.[8] Research papers like Brown, Goetzmann and Kumar (1998) that could truly ascertain the scientific nature of the Dow Theory having the ability to forecast the stock market have been few and far between. As in studying the technical analysis theory and methodology, almost all scholars have had no alternative but to resort to the Efficient Market Theory and mistakenly use it as the benchmark to validate whether technical analysis is scientific or not. Consequently, studies carried out by the financial scholars over the past 50 years have been inconducive to clarifying the scientific connotations of the Dow Theory.[9]

As a result of the above-mentioned technical difficulties and inclement industrial environment, there have been severe deviations and even stoppages in the effort to carry forward and develop the Dow Theory in terms of scientific thoughts and research direction in a scientific manner all along. Scientific thoughts associated with the stock market functions and stock market pricing on the part of the Dow Theory have thus been ignored and gradually forgotten.

Conclusion

A generally known fact is that, in recognition of their contributions to the financial economics, founders of the CAPM and the EMH have won the Nobel Prizes in economics.[10] Meanwhile, DJIA, conceived by Charles H. Dow in 1884 as the well-known economic leading indicator, has witnessed a rise from 40 points to 24,000 points today. What presents a sharp contrast in this regard is that the Dow Theory, along with other technical analysis theories, has long been regarded as Voodoo finance in the financial academic circles.

A rarely known fact is that, over the past 30-odd years, the Fed, as the largest financial market regulator and pilot across the globe, has consistently relied on the Dow Theory in administering and guiding the U.S. stock markets. According to the author's research findings, yearly data of DJIA (1982–2016) suggests that the Fed prefers to combine a five-year price uptrend with a one- to three-year price downtrend (or one-year positive correction trend) as a full stock market movement cycle to plan and develop the U.S. stock markets, as we can see in Table 1.

Table 1. U.S. stock market cycles (1982–2017)

No.	Time period (Year)	A full stock price cycle in DJIA closing price Bullish uptrend + Correction (positive or negative) trend	The duration of the major trend
1	1982–1987	1047,1259,1212,1547,1896] + [1939]	5 years uptrend
2	1988–1994	[2169,2753,2634,3169,3301,3754]+[3834]	6 years uptrend
3	1995–2002	[5117,6448,7908,9181,11497]+[10787,10022,8342]	5 years uptrend
4	2003–2008	[10454,10783,10718,12463,13265]+[8776]	5 years uptrend
5	2008–2012	[8776] + [10428,11578,12218,13104]	4 years uptrend
6	2013–2018	[16577,17824,17425,19763,24719]+[?]	5 years uptrend

From Table 1, we can clearly see that Charles H. Dow 's thinking that stock market moves in trend, and that the duration of the primary trend is about four to six years, is correct. More importantly, we can easily identify from Table 1 that the Fed is following the Dow Theory, but with elasticity when the Fed manages and guides the world biggest stock markets.[11]

Relying on our breakthrough achievements in studies on the actual investor behaviour and the stock price behavior, we have succeeded in setting up mathematic models for describing the inner mechanism and rules of the movement of the stock markets. Research conclusions drawn from the verification of the Dow Theory through these mathematic models indicate that the Dow Theory is not only rich in scientific content but is also generally applicable, straddling over different times. Charles H. Dow was a true genius in the global financial history. At the same time, the conclusions of the present paper collaborate the statement of Brown, Goetzmann and Kumar (1998) stating that the Dow Theory does have the ability to forecast the stock market.

The author sincerely hopes that what he has written in this paper serves as a source of eternal comfort and condolence for both Charles H. Dow and William Peter Hamilton, whose great contributions to the scientific understanding of the stock price behavior should never be taken lightly.

All that glitters is not gold, but gold certainly glitters. The Dow Theory is not Voodoo finance. Rather, the Dow Theory is the stock market theory with rich scientific content being buried by temporary prejudice and foolishness. For the Dow Theory to become the cornerstone of the new financial investment theory in the coming future, it is incumbent upon the financial academic circle, financial investment management circle, and technical analysis industry to make concerted efforts to work in this direction. This may well take one or two decades. Undoubtedly, however, this is a highly promising branch of learning to be tapped with bright prospects.

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Notes

1 This paper is the first of the series of papers on the traditional technical analysis theory. The purpose of this research project is to make an explorative revision and upgrade of the traditional technical analysis theory.

2 The Dow Theory was developed by Charles Dow, refined by William Peter Hamilton, and articulated by Robert Rhea. But it was S.A. Nelson who evolved the name of "Dow's Theory".

3 The present paper has made extensive references to the sentences and paragraphs in the book. The author hereby extends his heartfelt thanks to John Wiley & Sons, Inc., the holder of the copyright of the book.

4 The behavior of the stock market is the combination of the expectations on the part of the investor. If the investor's expectations are knowable, the stock market must be knowable. The reverse is equally valid.

5 The Dow Theory pundits and advocates use the statement that "The average discounts everything" in place of most of the contents of the scientific thoughts of the Dow Theory on the stock market (macro portion).

6 We could see that [Hamilton, page 23] writes: in the Review and Outlook of The Wall Street Journal of January 4, 1902, he says: "Nothing is more certain that the market has three well defined movements which fit into each other. The third swing is the great move covering from four to six years. [Hamilton, pages 23–24] comments: remember that Dow wrote this twenty years ago, and that he had not the records for analysis of the market movement which are now available. The extent of the primary movement, as given in this quotation, is proved to be far too long by subsequent experience; and a careful examination has shown me that the major swing before Dow wrote was never "from four to six years," rarely three years and oftener less than two. But Dow always had a reason for what he said, and his intellectual honestly assures those who knew him that it was at least an arguable reason.

Studies performed by the present writer validates that Dow's statements are correct for the simple reason that what Hamilton had observed was actually incomplete stock price movement trends (most of which were interrupted by economic factors and were therefore incomplete). As Hamilton could not distinguish between a complete stock price movement trend and an incomplete stock price movement trend and the root cause behind the incomplete stock price movement trend, the present author is of the opinion that Hamilton could have misunderstood Dow.

7 See Alfred Cowles (1934) "Can stock market forecasters forecast"?

8 Important research papers which support technical analysis include: Tabell and Tabell (1964), Treynor and Ferguson (1985), Pruitt and White (1988), Brown and Jennings (1989), Frankel and Froot (1990), Neftci (1991), Brock, Lakonishok, and LeBaron (1992), Blume, Easley, and O'Hara (1994), Neely, Weller, and Dittmar (1997), Clyde and Osler

(1997), Neely and Weller (1998), Lo, Mackinlay, and Wang (2000), Neely and Weller (2001), Neely and Weller (2003), and Zhou and Dong (2004). Park and Irwin (2004) made a very good review of those articles on technical analysis from 1960 to present.
Regarding the discussion of the unscientific nature of the EMH, please refer to the author's research paper, which had been accepted for presentation at the 20th Australian Finance and Banking Conferences at SSRN (Death of the Efficient Market Hypothesis).
Due to the fact that financial scholars have had to rely on the benchmark of the EMH and the existing financial analysis framework, such works are basically incapable of demonstrating the scientific roots of technical analysis.

9 Regarding the discussion of the unscientific nature of the CAPM, please refer to the author's research paper, which had been accepted for presentation at the 30th Australian Finance and Banking Conferences at SSRN (Death of the Capital Asset Pricing Model).

10 Please note that No. 1 cycle is composed of a 5-year price uptrend + 1-year positive correction price trend. No. 2 is composed of a 6-year price uptrend + 1-year positive correction price trend. No. 3 is composed of a 5-year price uptrend + 3-year price downtrend (or negative correction price trend). No. 4 is composed of a 5-year price uptrend + 1-year huge price downtrend. No. 5 is composed of a 1 big year price downtrend +4 years price uptrend. This special model is used to restore market confidence when stock markets are in extremely bearish. No. 6. If the Fed had not changed its working models of the stock markets, we could expect 2017 to be the last year of a 5-year price uptrend, and the possibility that 2018 will be a price downtrend correction year is above 80%.

Please also notice that, in the second cycle, the price uptrend is 6 years, and the correction price trend year in the cycles could be positive (not negative) in value, although the positive value is very small, and that cycle 4 and 5 share the same time period of 2008. Please pay attention to the fact that the uptrend is longer than the downtrend or correction trend in a stock market cycle, as the Dow Theory had made very clearly in this book.

If the readership has any inquiry about the classification of the duration of the bullish trends and the cycles of the DJIA in the past 35 years, please feel free to contact the author.

Day Trading Returns Across Volatility States

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Abstract

This paper measures the returns of a popular day trading strategy—the Opening Range Breakout (ORB) strategy—across volatility states. We calculate the average daily returns of the ORB strategy for each volatility state of the underlying asset when applied on long time series of crude oil and S&P 500 futures contracts. We find an average difference in returns between the highest and the lowest volatility state of around 200 basis points per day for crude oil, and of around 150 basis points per day for the S&P 500. This finding suggests that the success in day trading can depend to a large extent on the volatility of the underlying asset.

Introduction

Day traders are relatively few in number—approximately 1% of market participants—but account for a relatively large part of the traded volume in the marketplace, ranging from 20% to 50% depending on the marketplace and the time of measurement (e.g., Barber and Odean, 1999; Barber *et al.,* 2011; Kuo and Lin, 2013). Studies of the empirical returns of day traders using transaction records of individual trading accounts for various stock and futures exchanges can be found in Harris and Schultz (1998), Jordan and Diltz (2003), Garvey and Murphy (2005), Linnainmaa (2005), Coval *et al.* (2005), Barber *et al.* (2006, 2011) and Kuo and Lin (2013). When measuring the returns of day traders using transaction records, average returns are calculated from trades initiated and executed on the same trading day. Most of these studies report empirical evidence that some day traders are able to achieve average returns significantly larger than zero after adjusting for transaction costs, but that profitable day traders are relatively few—only one in five or less (e.g., Harris and Schultz, 1998; Garvey and Murphy, 2005; Coval *et al.,* 2005; Barber *et al.,* 2006; Barber *et al.,* 2011; Kuo and Lin, 2013). Linnainmaa (2005), on the other hand, finds no evidence of positive returns from day trading. We note that, if markets are efficient with respect to information, as suggested by the efficient market hypothesis (EMH) of Fama (1965; 1970), day traders should lose money on average after adjusting for trading costs. Therefore, empirical evidence of long-run profitable day traders is considered something of a mystery (Statman, 2002).

Why is it that some traders profit from day trading while most traders do not? We note that the difference between profitable traders and unprofitable traders can come from either trading different assets and/or trading differently (i.e., having different trading strategies). The account studies of Harris and Schultz (1998), Jordan and Diltz (2003), Garvey and Murphy (2005), Linnainmaa (2005), Coval *et al.* (2005), Barber *et al.* (2006, 2011), and Kuo and Lin (2013) do not relate trading success to any specific assets or to any specific trading strategy. Harris and Schultz (1998) and Garvey and Murphy (2005) report that profitable day traders react quickly to market information, but they do not investigate the underlying strategy of the traders studied.

Holmberg, Lönnbark, and Lundström (2013), hereafter HLL (2013), link the positive returns of a popular day trading strategy—the Opening Range Breakout (ORB) strategy—to intraday momentum in asset prices. The ORB strategy is based on the premise that, if the price moves a certain percentage from the opening price level, the odds favor a continuation of that movement until the closing price of that day (i.e., intraday momentum). The trader should therefore establish a long (short) position at some predetermined threshold placed a certain percentage above (below) the opening price and should exit the position at market close (Crabel, 1990). Because the ORB is used among profitable day traders (Williams, 1999; Fisher, 2002), assessing the ORB returns complements the account studies literature and could provide insights on the characteristics of day traders' profitability, such as average daily returns, possible correlation to macroeconomic factors, and robustness over time. For a hypothetical day trader, HLL (2013) find empirical evidence of average daily returns significantly larger than the associated trading costs when applying the ORB strategy to a long time series of crude oil futures. When splitting the data series into smaller time periods, HLL (2013) find significantly positive returns only in the last time period, ranging from 2001-10-12 to 2011-01-26, which are thus not robust to time. Because this time period includes the sub-prime market crisis, it is possible that ORB returns are correlated with market volatility.

This paper assesses the returns of the ORB strategy across volatility states. We calculate the average daily returns of the ORB strategy for each volatility state of the underlying asset when applied on long time series of crude oil and S&P 500 futures contracts. This undertaking relates to the recent literature that tests whether market efficiency may vary over time in correlation with specific economic factors (see Lim and Brooks, 2011 for a survey of the literature on time-varying market inefficiency). In particular, Lo (2004) and Self and Mathur (2006) emphasize that, because trader rationality and institutions evolve over time, financial markets may experience a long period of inefficiency followed by a long period of efficiency and vice versa. The possible existence of time-varying market inefficiency is of interest for the fundamental understanding of financial markets, but it also relates to how we view long-run profitable day traders. If profit is related to volatility, we expect profit in day trading to be the result of relatively infrequent trades that are of relatively large magnitude and are carried out during the infrequent periods of high volatility. If so, we could view positive returns from day trading as a tail event during time periods of high volatility in an otherwise efficient market. This paper contributes to the literature on day trading profitability by studying the returns of a day trading strategy for different volatility states. As a minor contribution, this paper improves the HLL (2013) approach of assessing the returns of the ORB strategy by allowing the ORB trader to trade both long and short positions and to use stop-loss orders in line with the original ORB strategy in Crabel (1990).

Applying technical trading strategies on empirical asset prices to assess the returns of a hypothetical trader is nothing new (for an overview, see Park and Irwin, 2007). This paper refers to technical trading strategies as strategies that are based solely on past information, i.e., technical analysis. As well as in HLL (2013), the returns of technical trading strategies applied intraday are discussed in Marshall *et al.* (2008b), Schulmeister (2009), and Yamamoto (2012). By assessing the returns of technical trading strategies, this paper achieves two advantages relative to studying individual trading accounts, as done in Harris and Schultz (1998), Jordan and Diltz (2003), Garvey and Murphy (2005), Linnainmaa (2005), Coval *et al.* (2005), Barber *et al.* (2006, 2011) and Kuo and Lin (2013). First, by assessing the returns of technical trading strategies, we may test longer time series than in account studies, thereby avoiding possible volatility bias in small samples. Second, we can study trading strategies that are specifically used for day trading, in contrast to the recorded returns of trading accounts. That is because trading accounts may also include trades initiated for reasons other than profit, such as consumption, liquidity, portfolio rebalancing, diversification, hedging, or tax motives, creating potentially noisy estimates (see the discussion in Kuo and Lin, 2013).

This paper recognizes two possible disadvantages when assessing the returns of a hypothetical trader using a technical trading strategy relative to studying individual trading accounts when the strategy is developed by researchers. First, if we want to assess the potential returns of actual traders, the strategy must be publicly known and used by traders at the time of their trading decisions (see the discussion in Coval *et al.,* 2005). Assessing the past returns of a strategy developed today tells little or nothing of the potential returns of actual traders because the strategy is unknown to traders at the time of their trading decisions. This paper avoids this problem by simulating the ORB strategy returns using data from January 1, 1991, and onward, after the first publication in Crabel (1990). Second, even if the strategy has been used among traders, the researcher could still potentially overfit the strategy parameters to the data and, in turn, overestimate the actual returns of trading. This is related to the problem of data snooping (e.g., Sullivan *et al.,* 1999; White, 2000). Because the ORB strategy is defined by only one parameter—the distance to the upper and lower threshold level—we avoid the problem of data snooping by assessing the ORB returns for a large number of parameter values.

By empirically testing long time series of crude oil and S&P 500 futures contracts, this paper finds that the average ORB return increases with the volatility of the underlying asset. Our results relate to the findings in Gencay (1998), in that technical trading strategies tend to result in higher profits when markets "trend" or in times of high volatility. This paper finds that the differences in average returns between the highest and lowest volatility state are around 200 basis points per day for crude oil, and around 150 basis points per day for S&P 500. This finding explains the significantly positive ORB returns in the period 2001-10-12 to 2011-01-26 found in HLL (2013). In addition, when reading the trading literature (e.g., Crabel, 1990; Williams, 1999; Fisher, 2002) and the account studies literature (e.g., Harris and Schultz, 1998; Garvey and Murphy, 2005; Coval *et al.,* 2005; Barber *et al.,* 2006; Barber *et al.,* 2011; Kuo and Lin, 2013), one may get the impression that long-run profitability in day trading is the same as earning steady profit over time. Related to volatility, however, the implication is that a day trader, profitable in the long-run, could still experience time periods of zero, or even negative average returns during periods of normal, or low, volatility. Thus, even if long-run profitability in day trading could be possible to achieve, it is achieved only by the trader committed to trade every day for a very long period of time or by the opportunistic trader able to restrict his trading to periods of high volatility. Further, this finding highlights the need for using a relatively long time series that contains a wide range of volatility states when evaluating the returns of day traders to avoid possible volatility bias.

We note that day traders may trade according to strategies other than the ORB strategy, and that positive returns from day trading strategies may coincide with factors other than volatility, but the ORB strategy is the only strategy and volatility the only factor considered in this paper. To the best of our knowledge, the ORB strategy is the only documented trading strategy actually used among profitable day traders. We continue this paper by presenting the ORB strategy, outlining the returns assessment approach, and presenting the tests. The section after that describes the data and gives the empirical results. The last section concludes.

The Orb Strategy

The ORB Strategy and Intraday Momentum

The ORB strategy is based on the premise that, if the price moves a certain percentage from the opening price level, the odds favor a continuation of that move until the market close of that day. The trader should therefore establish a long (short) position at some predetermined threshold a certain percentage above (below) the opening price and exit the position at market close (Crabel, 1990). Positive expected returns of the ORB strategy implies that the asset prices follow intraday momentum (i.e., rising asset prices tend to rise further and falling asset prices fall further) at the price threshold levels (e.g., HLL, 2013). We note that momentum in asset prices is nothing new (e.g., Jegadeesh and Titman, 1993; Erb and Harvey, 2006; Miffre and Rallis, 2007; Marshall *et al.,* 2008a; Fuertes *et al.,* 2010). Crabel (1990) proposed the Contraction-Expansion (C-E) principle to generally describe how asset prices are affected by intraday momentum. The C-E principle is based on the observation that daily price movements seem to alternate between regimes of contraction and expansion (i.e., periods of modest and large price movements) in a cyclical manner. On expansion days, prices are characterized by intraday momentum (i.e., trends), whereas prices move randomly on contraction days (Crabel, 1990). This paper highlights the resemblance between the C-E principle and volatility clustering in the underlying price returns series (e.g., Engle, 1982).

Crabel (1990) does not provide an explanation of why momentum may exist in markets. In the behavioral finance literature, we note that the appearance of momentum is typically attributed to cognitive biases from irrational investors, such as investor herding, investor over- and under-reaction, and confirmation bias (e.g., Barberis *et al.,* 1998; Daniel *et al.,* 1998). As discussed in Crombez (2001), however, momentum can also be observed with perfectly rational traders if we assume noise in the experts' information. The reason why intraday momentum may appear is outside the scope of this paper. We now present the ORB strategy.

We follow the basic outline of HLL (2013) and denote $P_t^o,\ P_t^h,\ P_t^l$ and P_t^c as the opening, high, low, and closing log prices of day *t,* respectively. Assuming that prices are traded continuously within a trading day, a point on day *t* is given by $t+\delta,\ 0 \le \delta \le 1$ and we may write: $P_t^o = P_t,\ P_t^c = P_{t+1},\ P_t^h = \max_{0\le\delta\le1} P_{t+\delta}$, and $P_t^l = \min_{0\le\delta\le1} P_{t+\delta}$. Further, we let ψ_t^u and ψ_t^l denote the threshold levels such that, if the price crosses it from below (above), the ORB trader initiates a long (short) position. These thresholds are placed at some predetermined distance from the opening price, $0<\rho<1$, i.e. $\psi_t^u = P_t^o + \rho$ and $\psi_t^l = P_t^o - \rho$. This paper refers to ρ as the *range;* it is a log return expressed in percentages. As positive ORB returns are based on intraday momentum (i.e., trends), the range should be small enough to enter the market when the move still is small, but large enough to avoid market noise that does not result in trends (Crabel, 1990). This paper assumes that day traders have no *ex ante* bias regarding future price trend direction and, in line with HLL (2013), uses symmetrically placed thresholds with the same ρ for long and short positions.

If markets are efficient with respect to the information set, $\Psi_{t+\delta}$, we know from the martingale pricing theory (MPT) model of Samuelson (1965) that no linear forecasting strategy for future price changes based solely on information set $\Psi_{t+\delta}$ should result in any systematic success. In particular, we may write the martingale property of log prices and log returns, respectively, as follows;

$$E_{t+\delta}[P_{t+1}|\Psi_{t+\delta}] = P_{t+\delta} \quad (1)$$
$$E_{t+\delta}[R_{t+1}|\Psi_{t+\delta}] = E_{t+\delta}[P_{t+1}|\Psi_{t+\delta}] - P_{t+\delta} = 0 \quad (2)$$

where $E_{t+\delta}$ is the expected value operator evaluated at time $t+\delta$.Relating ORB returns to intraday momentum, this paper tests whether prices follow momentum at the thresholds, ψ_t^u and (ψ_t^l),, such that:

$$E_{t+\gamma}[P_{t+1}|P_{t+\gamma} = \psi_t^u] > \psi_t^u \ or\ E_{t+\gamma}[P_{t+1}|P_{t+\gamma} = \psi_t^l] < \psi_t^l \quad (3)$$

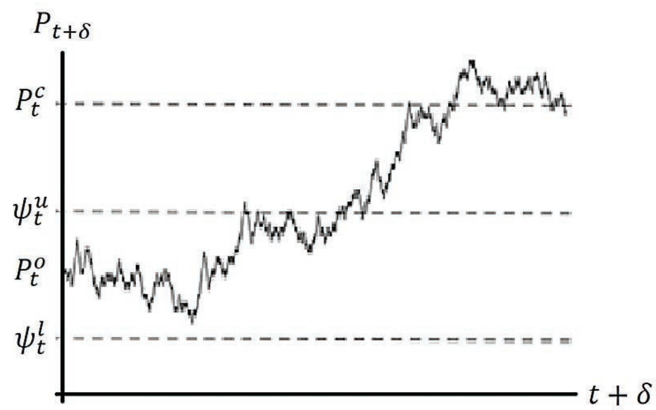
where $0 < \gamma < 1$ represents the point in time when a threshold is crossed for the first time during a trading day. We note that intraday momentum, as shown by Eq. (3) contradicts the MPT of Eq. (1).

Assessing the Returns

This paper assesses the returns of the ORB strategy using time series of futures contracts with daily readings of the opening, high, low, and closing prices. The basic observation is that, if the daily high (P_t^h) is equal to or higher than ψ_t^u, or if the daily low (P_t^l) is equal to or lower than ψ_t^l, we know with certainty that a buy or sell signal was triggered during the trading day. From the returns assessment approach of HLL (2013), we can calculate the daily returns for long ORB trades by $R_t^L = P_t^c - \psi_t^u | P_t^h \ge \psi_t^u$, and for short ORB trades by $R_t^S = \psi_t^l - P_t^c | P_t^l \le \psi_t^l$, assuming that traders can trade at continuous asset prices to a trading cost equal to zero. Further, the trader is expected to trade only on days when thresholds are reached, so the ORB strategy returns are not defined for days when the price never reaches ψ_t^u or ψ_t^l (e.g., Crabel, 1990; HLL, 2013).

Figure 1 illustrates how a profitable ORB position may evolve during the course of a trading day.

Figure 1. An ORB strategy trader initiates a long position when the intraday price reaches ψ_t^u and then closes the position at P_t^c, with the profit $P_t^c - \psi_t^u > 0$.



This paper recognizes two limitations when assessing the ORB strategy returns using R_t^L and R_t^S independently from each other. The first limitation is that R_t^L obviously only captures the returns from long positions and R_t^S only captures the returns from short positions. Because ORB strategy traders should be able to profit from long or short trades, whichever comes first, we expect that the HLL (2013) approach of assessing trades in only one direction at a time (either by using R_t^L or R_t^S) may underestimate the ORB strategy returns suggested in Crabel (1990) and in trading practice. The second limitation is that R_t^L and R_t^S are both exposed to large intraday risks, with possibly large losses on trading days when prices do not trend but move against the trader. Crabel (1990) suggests that the ORB trader should always limit intraday losses by using stop-loss orders placed a distance below (above) a long (short) position.

This paper improves the approach used in HLL (2013) to assess the returns of ORB strategy traders by allowing the trader to initiate both long and short trades with limited intraday risk, in line with Crabel (1990), still applicable to time series with daily readings of the opening, high, low, and closing prices. We denote it the "ORB Long Strangle" returns assessment approach because it is a futures trader's equivalent to a Long Strangle option strategy (e.g., Saliba *et al.,* 2009). The ORB Long Strangle is done in practice by placing two resting market orders: a long position at ψ_t^u and a short position at ψ_t^l, both positions remaining active throughout the trading day. Assuming that traders can trade at continuous asset prices and to a trading cost equal to zero, the Long Strangle produces one of three possible outcomes: 1) only the upper threshold is crossed, yielding the return R_t^L; 2) only the lower threshold is crossed, yielding the return R_t^S; or 3) both thresholds are crossed during the same trading day, yielding a return equal to $\psi_t^l - \psi_t^u < 0$. We note that, if a trader experiences an intraday double crossing, the trader should not trade during the remainder of the trading day (e.g., Crabel, 1990). Because there are only two active orders in the Long Strangle, we can safely rule out more than two intraday crossings. As before, ORB strategy returns are not defined for days when the price reaches neither threshold.

This paper calculates the daily returns of the Long Strangle strategy, $R_t^{L\&S}$, as:

$$R_t^{L\&S} = \begin{cases} P_t^c - \psi_t^u \gtreqless 0, if\ (P_t^h \geq \psi_t^u) \cap (P_t^l > \psi_t^l) \\ \psi_t^l - P_t^c \gtreqless 0, if\ (P_t^h < \psi_t^u) \cap (P_t^l \leq \psi_t^l) \\ \psi_t^l - \psi_t^u < 0, if\ (P_t^h \geq \psi_t^u) \cap (P_t^l \leq \psi_t^l) \end{cases} \quad (4)$$

The ORB Long Strangle approach in Eq. (4) allows us to assess the returns of traders initiating long or short positions, whichever comes first, using the opposite threshold as a stop loss order,[1] effectively limiting maximum intraday losses to $\psi_t^l - \psi_t^u = -2\rho < 0$ (for symmetrically placed thresholds). Therefore, the returns $R_t^{L\&S}$ provide a closer approximation of the ORB returns in Crabel (1990) relative to studying R_t^L and R_t^S independently and separately from each other. Henceforth, we refer to the ORB Long Strangle strategy as the ORB strategy if not otherwise mentioned. This paper assumes an interest rate of money equal to zero so that profit can only come from actively trading the ORB strategy and not from passive rent-seeking. In the empirical section, we also study ORB returns when trading costs are added, and we discuss the effects on ORB returns if asset prices are not continuous.

Measuring the Average Daily Returns Across Volatility States

This paper measures the average daily returns for different volatility states by grouping the ORB returns into 10 volatility states based on the deciles of the daily price returns volatility distribution. The volatility states are ranked from low to high, with the 1:*st* decile as the state with the lowest volatility and the 10:*th* decile as the state with the highest volatility. We then calculate the average daily return for each volatility state by the following dummy variable regression, given ρ:

$$R_{\rho,t}^{L\&S} = \sum_{\tau=1}^{10} a_{\rho,\tau} D_{\rho,\tau} + v_{\rho,t} \quad (5)$$

where $a_{\rho,\tau}$ is the average ORB return in the τ: *th* volatility state, $D_{\rho,\tau}$ is a binary variable equal to one if the returns corresponds to the τ: *th* decile of the volatility distribution, or zero otherwise, and $v_{\rho,\tau}$ is the error term. From the expected (positive) correlation between ORB returns and volatility, the ORB returns will experience heteroscedasticity and possibly serial correlation. To assess the statistical significance of Regression (5) we therefore apply Ordinary Least Squares (OLS) estimation using Newey-West Heteroscedasticity and Autocorrelated Consistent (HAC) standard errors.

The $D_{\rho,\tau}$ in Regression (5) requires that we estimate the volatility. Unfortunately, volatility, $\sigma_{t+\delta}$, is not directly observable (e.g., Andersen and Bollerslev, 1998). Another challenge for this study is to estimate intraday volatility over the time interval $0 \leq \delta \leq 1$, when limited to time series with daily readings of the opening, high, low, and closing prices.

Making good use of the data at hand, this paper uses the simplest available approach to estimate daily volatility σ_{t+1} by tracking the daily absolute return (log-difference of prices) of day *t:*

$$\sigma_t^c = +\sqrt{(P_t^c - P_t^o)^2} = |P_t^c - P_t^o| \quad (6)$$

Using absolute returns as a proxy for volatility is the basis of much of the modeling effort presented in the volatility literature (e.g., Taylor, 1987; Andersen and Bollerslev, 1998; Granger and Sin, 2000; Martens *et al.,* 2009), and has shown itself to be a better measurement of volatility than squared returns (Forsberg and Ghysels, 2007). Although σ_t^c is unbiased (i.e., $E_t \sigma_t^c = \sigma_{t+1}$), it is a noisy estimator (e.g., Andersen and Bollerslev, 1998). One extreme example would be a very volatile day, with widely fluctuating prices, but where the closing price is the same as the opening price. The daily open-to-close absolute return would then be equal to zero, whereas the actual volatility has been non-zero. Because positive ORB returns imply a closing price at a relatively large (absolute) distance from the opening price, we expect reduction in noise for the higher levels of positive ORB returns.

Because the ORB strategy trader is profiting from intraday price trends, it stands to reason that he should increase his return on days when volatility is relatively high. When using σ_t^c to estimate volatility, the relationship between intraday momentum [by Eq. (3)] and volatility is straightforward. For a profitable long trade, we have the relationship $R_t^{L\&S} = P_t^c - \psi_t^u = P_t^c - P_t^o - \rho = \sigma_t^c - \rho$ because $R_t^{L\&S} = P_t^c - \psi_t^u > 0$ and $P_t^c - P_t^o = \sigma_t^c > 0$. For a profitable short trade, we have the relationship $R_t^{L\&S} = -(P_t^c - \psi_t^l) = -(P_t^c - P_t^o + \rho) = -(-\sigma_t^c + \rho) = \sigma_t^c - \rho$ because $R_t^{L\&S} = -(P_t^c - \psi_t^l) > 0$ and $P_t^c - P_t^o = -\sigma_t^c < 0$. Thus, a positive ORB return equals the volatility minus the range for both long and short trades.

From this exercise, we learn that the ORB strategy trader should increase his expected return during days of relatively high volatility and decrease his expected return during days of relatively low volatility, suggesting different expected returns in different volatility states. In addition, we learn that positive ORB returns imply high volatility, but not the other way around, since the ORB strategy trader can still experience losses when volatility is high, associated with intraday double crossing: $R_t^{L\&S} = \psi_t^l - \psi_t^u = -2\rho < 0$.

When a price series is given in a daily open, high, low, and close format, Taylor (1987) proposes that the (log) price range in day t ($\varsigma_t = P_t^h - P_t^l > 0$) could also serve as a suitable measure of the daily volatility. To strengthen the empirical results, this paper also estimates daily volatility σ_{t+1} by the price range of day t(i.e., ς_t). Finding qualitatively identical results whether we use ς_t or σ_t^c, we report only the empirical results when using σ_t^c.

Empirical Results

Data

We apply the ORB strategy to long time series of crude oil futures and of S&P 500 futures. Futures contracts are used in this paper because long time series are readily available, and because futures are the preferred investment vehicle when trading the ORB strategy in practice (e.g., Crabel, 1990; Williams, 1999; Fisher, 2002). There are many reasons why futures are the preferable investment vehicle relative to, for example, stocks. Futures are as easily sold short as bought long, are not subject to short-selling restrictions, and can be bought on a margin, providing attractive leverage possibilities for day traders who wish to increase profit. In addition, costs associated with trading, such as commissions and bid-ask spreads, are typically smaller in futures contracts than in stocks due to the relatively high liquidity.

The data includes daily readings of the opening, high, low, and closing prices during the U.S. market opening hours. We note that ORB traders should trade only during the U.S. market opening hours, when the liquidity is high, even if futures contracts may trade for 24 hours (Crabel, 1990). Thus, the U.S. market opening period is the only time interval of interest for the study of this paper. The crude oil price series covers the period January 2, 1991, to January 26, 2011, and the S&P 500 price series covers the period January 2, 1991, to November 29, 2010. Both series are obtained from Commodity Systems Inc. (CSI) and are adjusted for rollover effects such as contango and backwardation by CSI. The future contract typically rolls out on the 20th of each month, one month prior to the expiration month; see Pelletier (1997) for technical details. We analyze the series separately and independent of each other. Figures 2 and 3 illustrate the price series over time for crude oil and S&P 500 futures, respectively.

Figure 2. The daily closing prices for crude oil futures over time, adjusted for rollover effects, from January 2, 1991, to January 26, 2011. Source: Commodity Systems Inc.

Figure 3. The daily closing prices for S&P 500 futures over time, adjusted for rollover effects, from January 2, 1991, to November 29, 2010. Source: Commodity Systems Inc.

Notable in Figure 2 is the sharp price drop for the crude oil series during the 2008 sub-prime crisis. In Figure 3, there are two price drops for the S&P 500 series, during the 2000 dot-com crisis and the 2008 sub-prime crisis.

Table 1 presents some descriptive statistics for the daily price returns of both assets, and Figures 4 and 5 graphically illustrate the daily price returns volatility over time for crude oil and S&P 500, respectively.

Table 1. Descriptive statistics of the daily price returns

	Obs.	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
crude oil	4845	0.0002	0.0077	-0.0606	0.0902	0.22	9.67
S&P 500	5018	0.0001	0.0093	-0.0912	0.0808	-0.06	11.73

Figure 4. The daily price returns volatility (%) for crude oil futures over time, from January 2, 1991, to January 26, 2011.

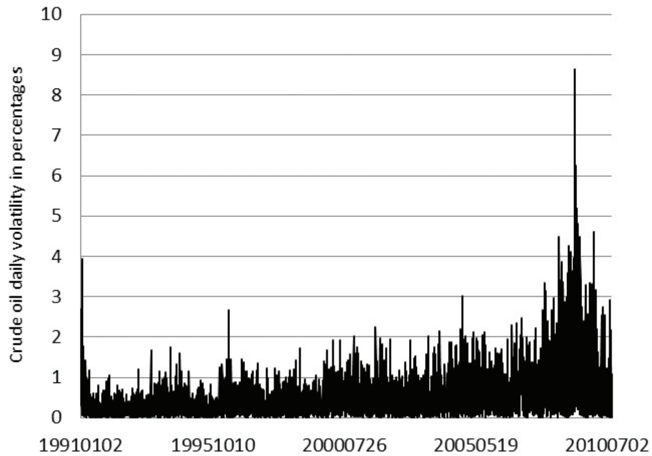


Figure 5. The daily price returns volatility (%) for S&P 500 futures over time, from January 2, 1991, to November 29, 2010.

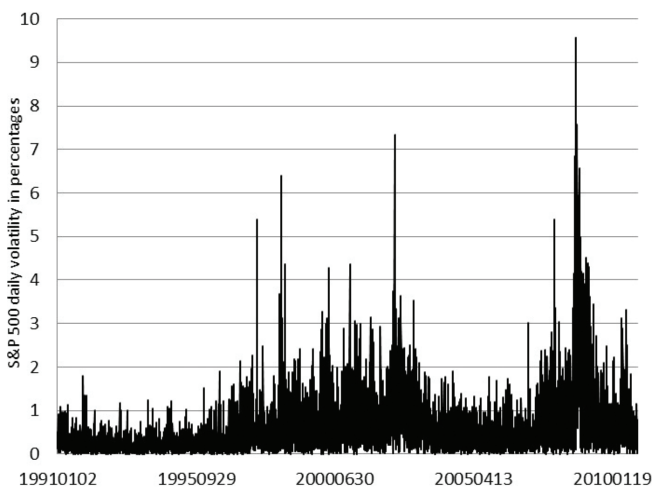


Table 1 shows that daily price returns display the expected characteristics of empirical returns series, with close-to-zero means and positive kurtosis for both assets. As expected, we can confirm that the means for crude oil and S&P 500 are not significantly larger than zero, although this is not explicitly shown. Figures 4 and 5 reveal apparent volatility clustering over time for both assets. These results are expected for empirical returns (e.g., Cont, 2001).

The Average Daily Returns Across Volatility States

This paper assesses strategy returns for different levels of ρ, ranging from small to large, thereby spanning the profit opportunities of ORB strategies. For simplicity and without loss of information, we only present the results for thresholds $\rho \epsilon \{0.5\%, 1.0\%, 1.5\%, 2.0\%\}$, for both assets. Figures 6–9 and Figures 10–13 present the average daily ORB returns across volatility states for crude oil futures and for S&P 500 futures, respectively. We illustrate the ORB returns in basis points (%%), ($\alpha \cdot 10\,000$), where α is the average ORB return for a given volatility state (see the definition of α in the previous section). We use 95% point-wise confidence intervals based on the HAC standard errors.

Figure 6. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using ρ = 0.5%. We use 95% confidence intervals based on the HAC standard errors.

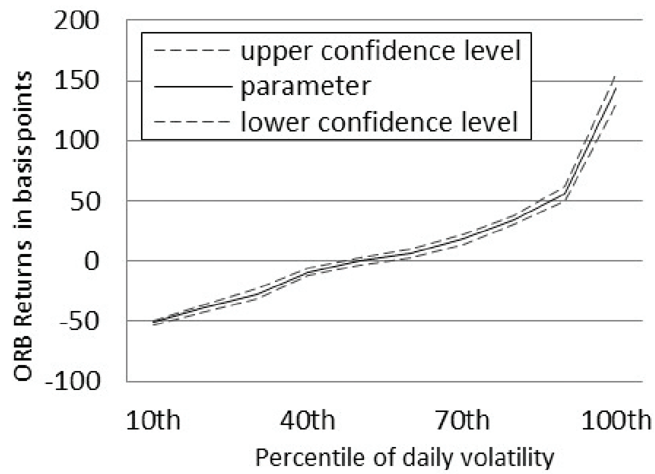


Figure 7. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using ρ = 1.0%. We use 95% confidence intervals based on the HAC standard errors.

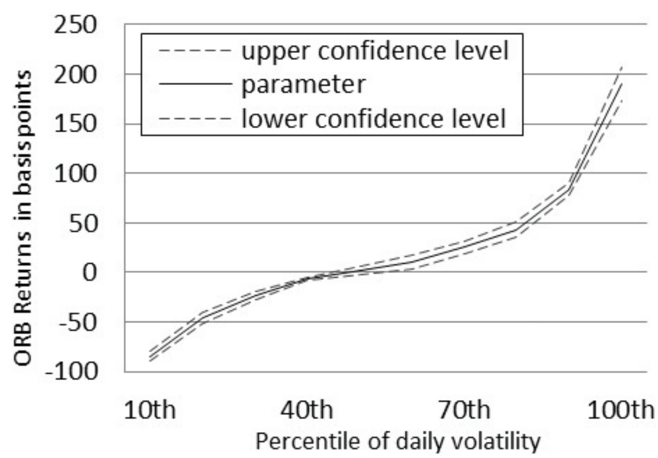


Figure 8. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using ρ = 1.5%. We use 95% confidence intervals based on the HAC standard errors.

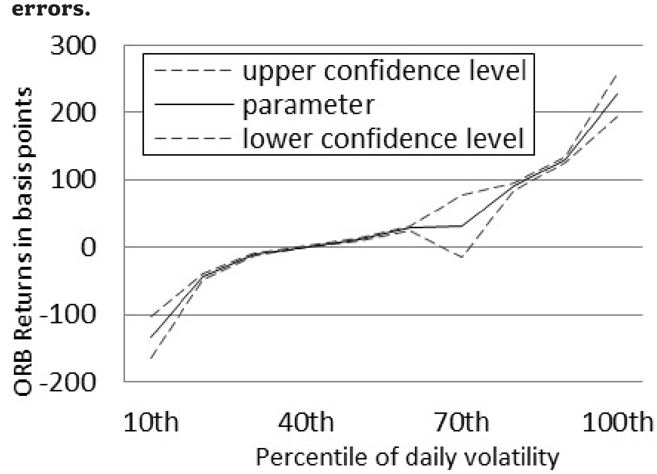


Figure 9. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using ρ = 2.0%. We use 95% confidence intervals based on the HAC standard errors.

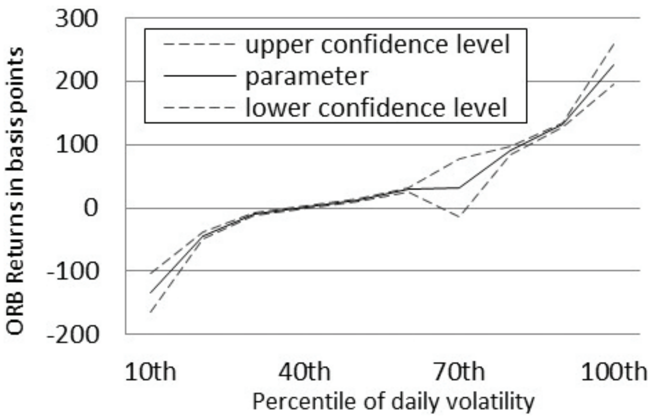


Figure 10. Average returns (bp:s) across volatility states (τ) when trading S&P 500 futures using ρ = 0.5%. We use 95% confidence intervals based on the HAC standard errors.

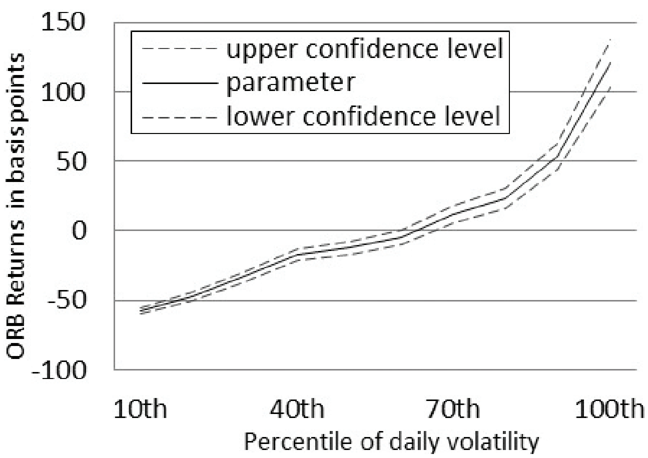


Figure 11. Average returns (bp:s) across volatility states (τ) when trading S&P 500 futures using ρ = 1.0%. We use 95% confidence intervals based on the HAC standard errors.

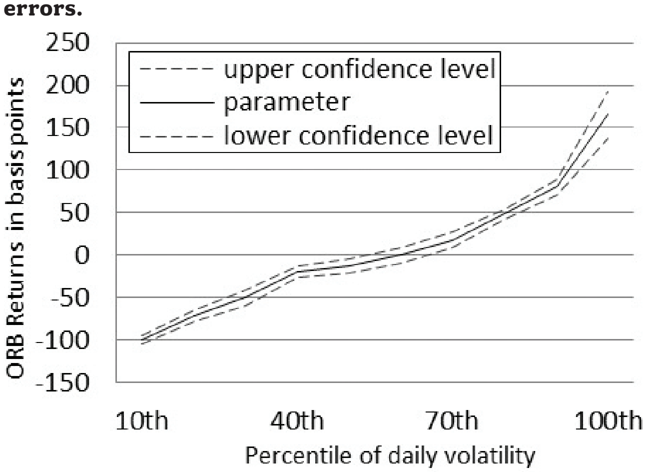


Figure 12. Average returns (bp:s) across volatility states (τ) when trading S&P 500 futures using ρ = 1.5%. We use 95% confidence intervals based on the HAC standard errors.

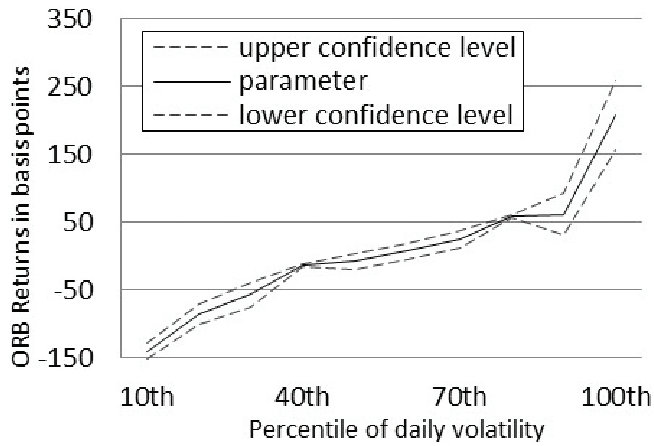
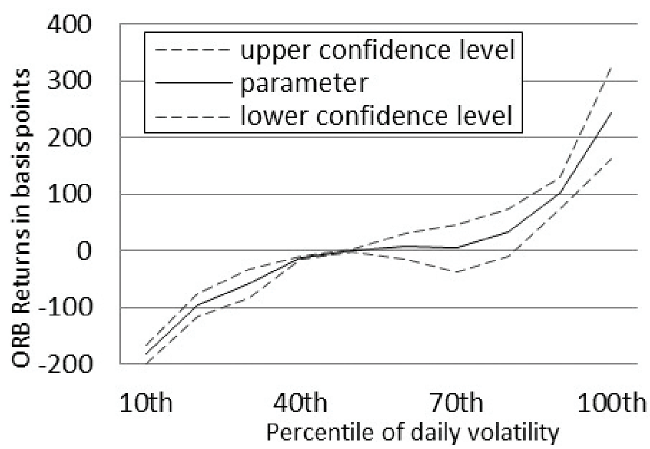


Figure 13. Average returns (bp:s) across volatility states (τ) when trading S&P 500 futures using ρ = 2.0%. We use 95% confidence intervals based on the HAC standard errors.



Figures 6–13 show significantly negative returns for lower volatility states, $\tau \geq 3$, and significantly positive returns for higher volatility states, $\tau \leq 7$, for both assets. That is, the average daily returns from day trading using ORB strategies are correlated with volatility. The difference in average daily returns between state and are remarkably high—around 200 basis points per day for crude oil and around 150 basis points per day for S&P 500, given ρ = 0.5%. For larger ρ:*s*, the differences grow even larger.

Because the returns are calculated daily, relatively small differences in the average daily returns have substantial effects on wealth when annualized. The annualized return from a 200-point daily difference between state 1 and state 10 amounts to $(1 + 0.02)^{240} - 1 = 115\%$, and a 150 point daily difference amounts to $(1 + 0.015)^{240} - 1 = 35\%$, given 240 trading days in a year. Thus, the annualized returns differ substantially for a day trader consistently trading in the lowest volatility state compared to one trading in the highest volatility state. This is merely an example to illustrate the effect that daily returns have on annualized returns; however, it should not be taken as the result of actual trading. This is because the results so far are based on the assumption that the trader *a priori* knows the volatility state; in this respect, these are in-sample results. In actual trading, traders do not *a priori* know the volatility state and are not able to trade assets in high volatility states every day.

To shed more light on profitability when using the ORB strategy in actual trading, this paper also assesses the ORB strategy returns without *a priori* knowledge of the volatility state among traders (i.e., the results of trading out-of-sample). We assess both daily and annual returns because both are relevant for traders—a strategy yielding a high daily return on average is of limited use to a trader who trades only once a year.

Returns When Trading the ORB Strategy Out-of-Sample

When trading the ORB strategy, the idea is to restrict trading only to expansion days (high volatility) and avoid trading during contraction days (normal or low volatility). When trading out-of-sample, however, the trader does not *a priori* know the volatility state, so some form of volatility prediction is necessary. The trader can either try to predict volatility states using econometric approaches (e.g., Engle, 1982; Andersen and Bollerslev, 1998) or use the ORB strategy approach (Crabel, 1990; Williams, 1999; Fisher, 2002), identifying the range as a volatility predictor by itself and setting the range large enough so that only large volatility days are able to reach the thresholds.

This paper assesses the average daily returns when trading the ORB strategy out-of-sample,[2] following the approach of Crabel (1990), Williams (1999), and Fisher (2002) (i.e., setting the range large enough so that only large volatility days are able to reach the thresholds). We estimate the average daily returns with the regression $R_{\rho,t}^{L\&S} = A_\rho + \omega_{\rho,t}$, where A_ρ is the average daily return of the ORB strategy during days with predicted high volatility, and ω_t is the error term, given a certain range. The results for both assets are given in Table 2:

Table 2. Daily returns when trading the ORB strategy out-of-sample. ρ is the percent distance added to and subtracted from the opening price. *T* is the number of trades. *freq* gives the proportion of trades that result in positive returns, while *A* gives the average daily return. The p-values are calculated based on the HAC standard errors. No trading costs are included.

	ρ(%)	T	freq.	A	p
	0.5	2827	0.57	0.0013	0.0000
crude oil	1.0	1044	0.58	0.0020	0.0000
	1.5	423	0.61	0.0027	0.0000
	2.0	189	0.67	0.0036	0.0001
	0.5	3314	0.49	0.0004	0.0057
S&P 500	1.0	1572	0.53	0.0006	0.0267
	1.5	749	0.52	0.0006	0.1755
	2.0	368	0.52	0.0006	0.4937

Table 2 shows mixed results when trading the ORB strategy out-of-sample. We find significantly positive returns for all ranges at the 95% confidence level when trading crude oil futures out-of-sample, and it seems that returns increase with ρ. When trading S&P 500 futures out-of-sample, however, we find significantly positive returns only for the two smaller ranges, ρ = 0.5 and ρ = 1.0, at the 95% confidence level. For ranges larger than ρ = 1.0 (e.g., ρ = 1.5, ρ = 2.0), we cannot reject the null hypothesis of zero returns on average. When separating the (Long Strangle) returns between long and short trades when trading S&P 500, we find that the average returns of short trades, initially positive, are reduced for ρ > 1.0%, while the returns of long trades seem to increase with ρ, as in the crude oil example. This difference in average returns between long and short ORB trades drives the results, although this is not explicitly shown. Regardless of the reasons why, it is clear that not all ranges are profitable when trading the S&P 500 out-of-sample. Thus, profitability when trading the ORB strategy out-of-sample depends on the choice of asset and range. Using the "wrong" range for a particular asset (e.g., using ρ = 1.5 or ρ = 2.0 when trading S&P 500), the ORB strategy does not necessarily yield a daily return significantly larger than zero on average.

To compare these returns with the returns of an alternative investment strategy, we also study the difference between the return of the ORB strategy ($R_t^{L\&S}$) for day t and the corresponding return of the so-called buy and hold strategy ($R_t^{B\&H} = P_t^c - P_{t-1}^c$). The buy and hold strategy is a straightforward strategy where the trader buys the asset and holds it until the expiration of the future contract, at which point the position is "rolled over" onto the next contract. As it turns out, the buy and hold strategy returns are close to zero; when running the regression $R_t^{L\&S} - R_t^{B\&H} = \tilde{A} + \tilde{\omega}_t$, we find qualitatively the same results as illustrated in Table 2, for both assets, although not explicitly shown. That is, when trading crude oil futures out-of-sample, we find empirical support that the ORB strategy yields a larger average daily return for all ranges compared to the buy and hold strategy. When trading S&P 500 futures out-of-sample, on the other hand, we find empirical support that the ORB strategy yields a larger average daily return only for ρ = 0.5 and ρ = 1.0, compared to the buy and hold strategy.

We now investigate what a day trader can expect in terms of accumulated annual returns when trading the ORB strategy out-of-sample. We start by plotting the wealth accumulation over time starting at 1991-01-01 with a value of 1,000,000 USD, for all ranges, and for both assets. Profit is reinvested on to the next trade. The wealth accumulation of the buy and hold (B&H) strategy is included as a reference. Figures 14 and 15 plot the wealth accumulation over time when applying the B&H and the ORB strategy to trade crude oil futures and S&P 500 futures, respectively, out-of-sample. Table 3 presents the corresponding out-of-sample annual returns statistics (calendar year).

Figure 14. Wealth over time, starting with 1,000,000 USD (expressed in log levels), when trading crude oil futures out-of-sample using ORB strategies for all ranges from January 1, 1991, to January 26, 2011. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy given a particular range. No trading costs are included.

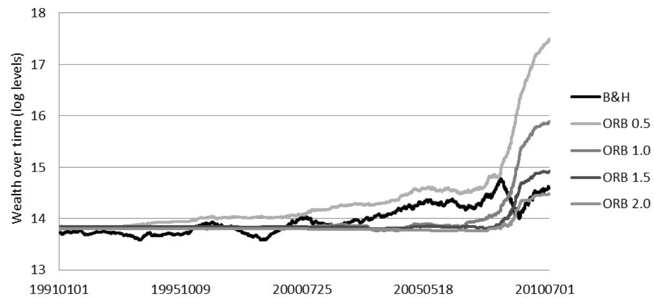


Figure 15. Wealth over time, starting with 1,000,000 USD (expressed in log levels), when trading S&P 500 futures out-of-sample using ORB strategies for all ranges from January 1, 1991, to November 29, 2010. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy for a particular range. No trading costs are included.

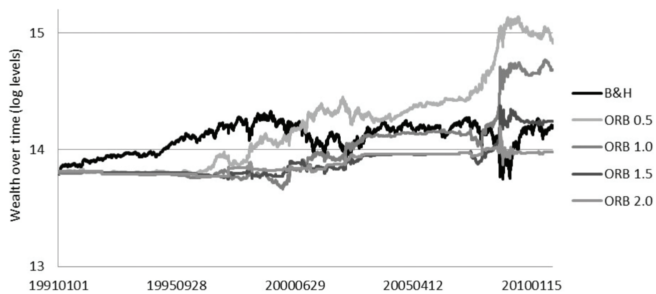


Table 3. Annual returns (calendar year) when trading the B&H strategy and the ORB strategy out-of-sample. ρ is the percent distance added to and subtracted from the opening price, where N/A refers to the B&H strategy. Mean/Std.Dev gives the average annual return per unit of annual volatility and Mean/-Min gives the average annual return over the largest annual loss. No trading costs are included.

	ρ(%)	Obs.	Mean	Std.Dev.	Min	Max	Mean/Std.Dev.	Mean/-Min
	N/A	19	0.0530	0.1672	-0.2505	0.3864	0.32	0.21
	0.5	19	0.3055	0.7110	-0.0493	2.5527	0.43	6.19
crude oil	1.0	19	0.1568	0.4244	-0.0758	1.3994	0.37	2.07
	1.5	19	0.0725	0.2180	-0.0214	0.7740	0.33	3.39
	2.0	19	0.0391	0.1179	-0.0189	0.3866	0.33	2.07
	N/A	19	0.0250	0.1061	-0.1791	0.2665	0.24	0.14
	0.5	19	0.0661	0.1655	-0.0784	0.6995	0.40	0.84
S&P 500	1.0	19	0.0562	0.1876	-0.1222	0.7946	0.30	0.46
	1.5	19	0.0243	0.0848	-0.0557	0.3673	0.29	0.44
	2.0	19	0.0087	0.0253	-0.0208	0.0720	0.34	0.42

Figures 14 and 15 illustrate that wealth accumulates unevenly over time, and primarily during time periods connected to market crisis events with high volatility, for both assets. Even when ORB traders profit in the long run, we observe long periods of negative growth in wealth for both assets. Hence, profitability is not robust to time. Moreover, Figures 14 and 15 graphically show that long-run profit using ORB strategies is the result of relatively infrequent trades of a relatively large magnitude, associated with the infrequent time periods of market crisis (i.e., periods of high volatility).

Table 3 shows that the optimal levels of the range for maximizing annual returns are the relatively small range, ρ = 0.5%, for both assets. Table 3 further illustrates that traders using the B&H strategy can achieve larger annual returns on average (Mean) than traders using ORB strategies for some ranges (ρ = 2.0% for crude oil, and ρ = 1.5% and ρ = 2.0% for S&P 500). One reason for the relatively low annual returns when trading ORB strategies is the relatively low frequency of trading (especially when using large ranges). As we increase the range, we remember from Table 2 that the number of trades (T) decreases. Fewer trades, in turn, decreases annual returns, *ceteris paribus.* We note that low annual returns due to few trades can, to some extent, be offset by trading many assets simultaneously, but this is not studied in this paper.

Table 3 further shows that ORB strategies yield larger risk-adjusted returns (measured by Mean/Std.Dev and Mean/-Min) than the buy and hold strategy, for all ranges and for both assets. This is interesting from a risk-return point of view because risk-averse day traders could benefit from using ORB strategies compared to the buy and hold strategy. ORB strategies seem especially attractive in terms of high Mean/-Min due to relatively moderate largest annual losses (min).

Sensitivity Analysis Regarding Price Jumps

Prices are not always continuous within a trading day but may experience so-called price jumps in the direction of the most recent price movement (e.g., Mandelbrot, 1963; Fama and Blume, 1966). Because of the price jumps, the trader may experience an order fill at worse prices than expected. Consequently, we may over-estimate the actual return from trading if the effects of price jumps are not taken into account when assessing the returns of technical trading strategies based on intraday thresholds (see, for example, the technical trading strategy in Alexander, 1961). This paper recognizes that possible price jumps will affect the returns of trading, but not necessarily in a negative way when we consider the ORB strategy.

This paper estimates the effects of price jumps on ORB returns in two stages of the trade. First, we model the price jump effect in market entries and, second, in market exits. First, because price jumps occur in the direction of the most recent price movement, the ORB traders' entry prices are sometimes filled at some other price than the threshold. If $\tilde{\psi}_t$ denotes the actual entry price on day t, we may write the price jump effects for long trades as $\tilde{\psi}_t^u > \psi_t^u$, and for short trades as $\tilde{\Psi}_t^l < \psi_t^l$, where the actual trading price is based on the range plus a price jump, $\tilde{\rho} = \rho + \varepsilon$, where $\varepsilon > 0$ is the size of the price jump. We consider here a reasonable estimate of ε = 2 basis points when trading crude oil and S&P 500 futures (based on empirical observations when trading futures with the ORB strategy using an account size of around 1,000,000 USD, Interactive Brokers, www.interactivebrokers.com, February 2, 2010, to November 29, 2010).

Second, because ORB traders exit the market at the market close, there cannot be a jump to some other level. Thus, P_t^c is the actual closing price of day . Moreover, in contrast to the technical trading strategy of Alexander (1961), where both market entry and exit are based on intraday threshold crossing, the ORB strategy is only affected by possible price jumps at the market entry level. From Figures 6 through 13 and Table 2, we observe that the effect of price jumps of ε = 2 basis points on returns is not necessarily negative when trading the ORB strategy. In fact, we find that the price jump effect on the average returns is positive for larger ρ when trading crude oil and either negative or positive, depending on the initial level of ρ, when trading S&P 500.

From this reasoning, we do not expect price jumps to qualitatively change the results shown in Figures 6 through 13 and Table 2 (i.e., returns significantly larger [smaller] than zero will most likely remain significantly larger [smaller] than zero.

Sensitivity Analysis Regarding Trading Costs

Trading costs in terms of commission fees and bid-ask spreads will consume some of the profits. For the assets under consideration, these costs are relatively small during the trading hours of the U.S. markets. We estimate that we need to subtract 4 basis points per trade, or 8 basis points roundtrip daily cost, for crude oil futures. For the S&P 500, we need to subtract 1.5 basis points per trade, or 3 basis points roundtrip daily cost (based on empirical observations when trading futures with the ORB strategy, using an account size of around 1,000,000 USD, Interactive Brokers, www.interactivebrokers.com, February 2, 2010, to November 29, 2010).

We recognize that these levels of trading costs are not large enough to qualitatively change the results for the average daily returns shown in Figures 6 through 13 or in Table 2; that is, returns significantly (insignificantly) larger than zero will remain significantly (insignificantly) larger than zero, even if trading costs are included. We find, however, that even small levels of trading costs have a large effect on the accumulation of wealth over time and on the corresponding annual returns, when trading ORB strategies out-of-sample.

Figures 16 and 17 graphically show the accumulation of wealth over time when trading ORB strategies out-of-sample, adjusted for trading costs, applied to crude oil and S&P 500, respectively. Table 4 gives the corresponding annual returns statistics for both assets.

Figure 16. Wealth over time, starting with 1,000,000 USD (expressed in log levels), when trading crude oil futures out-of-sample, with trading costs included, from January 1, 1991, to January 26, 2011. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy given a particular range. We subtract 8 basis points roundtrip daily cost during trading days for ORB strategies, and a roundtrip daily cost of 8/20 basis points for the B&H strategy (we assume that contracts are rolled each month and that each month consists of 20 trading days).

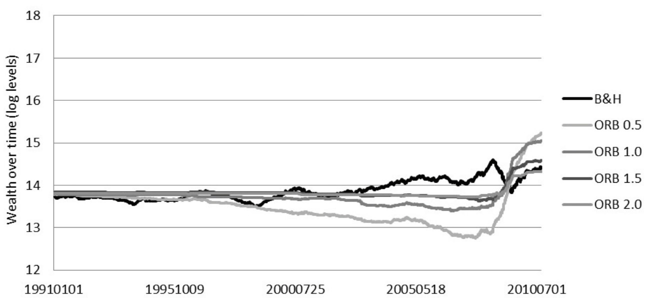


Figure 17. Wealth over time, starting with 1,000,000 USD (expressed in log levels), when trading S&P 500 futures out-of-sample, with trading costs included, from January 1, 1991, to November 29, 2010. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy for a particular range. We subtract 3 basis points roundtrip daily cost during trading days for ORB strategies, and a roundtrip daily cost of 3/20 basis points for the B&H strategy (we assume that contracts are rolled each month and that each month consists of 20 trading days).

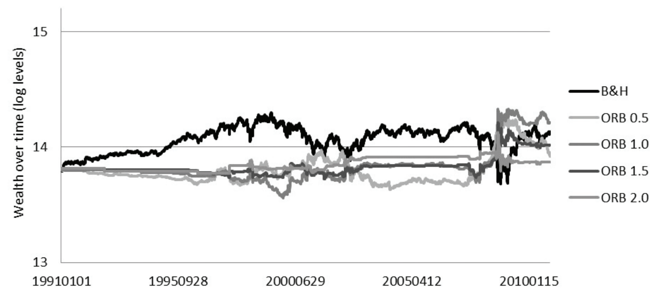


Table 4. Annual returns statistics (calendar year) when trading the B&H strategy and the ORB strategy out-of-sample when trading costs are included. ρ is the per cent distance added to and subtracted from the opening price, where N/A refers to the B&H strategy. Mean/Std.Dev gives the average annual return per unit of annual volatility and Mean/-Min gives the average annual return over the largest annual loss. When trading crude oil futures, we subtract 8 basis points roundtrip daily cost during trading days for ORB strategies, and a roundtrip daily cost of 8/20 basis points for the B&H strategy. When trading S&P 500 futures, we subtract 3 basis points roundtrip daily cost during trading days for ORB strategies, and a roundtrip daily cost of 3/20 basis points for the B&H strategy (we assume that contracts are rolled each month and that each month consists of 20 trading days).

	ρ(%)	Obs.	Mean	Std.Dev.	Min	Max	Mean/Std.Dev.	Mean/-Min
	N/A	19	0.0429	0.1658	-0.2580	0.3739	0.26	0.17
	0.5	19	0.1568	0.5930	-0.2016	2.0990	0.26	0.78
crude oil	1.0	19	0.0993	0.3490	-0.1128	1.1638	0.28	0.88
	1.5	19	0.0505	0.1798	-0.0718	0.6123	0.28	0.70
	2.0	19	0.0298	0.0980	-0.0221	0.3315	0.30	1.35
	N/A	19	0.0212	0.1057	-0.1822	0.2617	0.20	0.12
	0.5	19	0.0135	0.1482	-0.1416	0.5779	0.09	0.10
S&P 500	1.0	19	0.0300	0.1687	-0.1528	0.6954	0.18	0.20
	1.5	19	0.0123	0.0738	-0.0670	0.3120	0.17	0.18
	2.0	19	0.0031	0.0239	-0.0212	0.0681	0.13	0.15

Figures 16 and 17 graphically show considerably reduced wealth levels for both assets when trading costs are included, compared to the wealth levels in Figures 14 and 15. When trading crude oil, terminal wealth is reduced 49% (ρ = 0.5%), 37% (ρ = 1.0%), 30% (ρ = 1.5%), and 24% (ρ = 2.0%). When trading S&P 500, terminal wealth is reduced 80% (ρ = 0.5%), 47% (ρ = 1.0%), 49% (ρ = 1.5%), and 64% (ρ = 2.0%). For the buy and hold strategy, wealth is reduced 19% and 15% for crude oil and S&P 500, respectively.

Table 4 shows that annual returns and risk-adjusted returns decrease considerably for both assets when trading costs are included. Further, we find that the optimal range for maximizing annual returns remains at ρ = 0.5% for crude oil but increases to ρ = 1.0% for S&P 500 due to the increase in trading costs. In sum, trading costs decrease wealth accumulation and annual returns considerably but do not affect average daily returns shown in Table 2 in a qualitative way.

Conclusion

This paper assesses the returns of the ORB strategy across volatility states. We calculate the average daily returns of the ORB strategy for each volatility state of the underlying asset when applied on long time series of crude oil and S&P 500 futures contracts. This paper contributes to the literature on day trading profitability by studying the returns of a day trading strategy for different volatility states. As a minor contribution, this paper improves the HLL (2013) approach of assessing ORB strategy returns by allowing the ORB trader to trade both long and short positions and to use stop loss orders, in line with the original ORB strategy in Crabel (1990) and in trading practice.

When empirically tested on long time series of crude oil and S&P 500 futures contracts, this paper finds that the average ORB return increases with the volatility of the underlying asset. Our results relate to the findings in Gencay (1998), in that technical trading strategies tend to result in higher profits when markets "trend" or in times of high volatility. This paper finds that the differences in average returns between the highest and lowest volatility state are around 200 basis points per day for crude oil, and around 150 basis points per day for S&P 500. This finding explains the significantly positive ORB returns within the period 2001-10-12 to 2011-01-26 found in HLL (2013), but also, perhaps more importantly, relates to the way we view profitable day traders.

When reading the trading literature (e.g., Crabel, 1990; Williams, 1999; Fisher, 2002) and the account studies literature (e.g., Coval *et al.,* 2005; Barber *et al.,* 2011; Kuo and Lin, 2013), one may get the impression that long-run profitability in day trading is the same as earning steady profit over time. The findings of this paper suggest instead that long-run profitability in day trading is the result of trades that are relatively infrequent but of relatively large magnitude and are associated with the infrequent time periods of high volatility. Positive returns in day trading can hence be seen as a tail event during periods of high volatility of an otherwise efficient market. The implication is that a day trader, profitable in the long run, could still experience time periods of zero, or even negative, average returns during periods of normal, or low, volatility. Thus, even if long-run profitability in day trading could be achieved, it is achieved only by the trader committed to trade every day for a very long period of time or by the opportunistic trader able to restrict his trading to periods of high volatility. Further, this finding highlights the need for using a relatively long time series that contains a wide range of volatility states when evaluating the returns of day traders, in order to avoid possible volatility bias.

With trading ORB strategies out-of-sample, we find that profitability depends on the choice of asset and range, and that not all ranges are profitable. We find that the ORB strategy is profitable for all ranges when trading crude oil, but, when trading the S&P 500, the ORB strategy does not necessarily yield a daily return significantly larger than zero, on average, for some of the ranges. Further, we find that profitability is not robust to time. Even when ORB strategies are profitable in the long run, they still lose money during periods of time when volatility is normal or low. If the trader, for example, is unfortunate enough to start trading the ORB strategy after a market crisis event, when the volatility has moved back to a low volatility state, it could take a long time, sometimes years, of day trading until the trader starts to profit. We believe this finding to be worrisome news for a trader looking to day trading as an alternative source of regular income instead of employment. A point to note is that ORB strategies result in relatively few trades, which restricts potential wealth accumulation over time. Most likely, the ORB trader simultaneously monitors and trades on several different markets, thereby increasing the frequency of trading. Further, this paper studies profitability when trading the ORB strategy without leverage (leverage means that the trader could have a market exposure larger than the value of trading capital), which also may restrict potential wealth accumulation over time. Most likely, the ORB trader uses leverage to increase the returns from trading. Moreover, we find that trading costs do not affect average daily returns in a qualitative way but decrease annual returns considerably.

For future research, it would be of interest to study whether the returns of other strategies used by day traders also correlate with volatility. In addition, it would be of interest to study whether the returns of momentum-based strategies with longer investment periods than intraday (see, for example, the strategies in Jegadeesh and Titman, 1993; Erb and Harvey, 2006; Miffre and Rallis, 2007) correlate with volatility.

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Notes

[1] One could think of other possible placements of stop loss orders but this placement is the only one tested in this paper.

[2] We tried various ARCH and GARCH specifications to predict the volatility state, but without improving the results in any significant way. We find that expansion days, which result in high ORB returns, tend to come unexpectedly after a number of contraction days. Further, expansion days do not typically appear two days in a row. Thus, the volatility prediction models do not have time to react. This is perhaps the reason why the ARCH and GARCH specifications are unable to improve the trading results.

Disclaimer: Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the Swedish Pensions Agency.

Breakthroughs in Technical Analysis: New Thinking from the World's Top Minds—Edited by David Keller

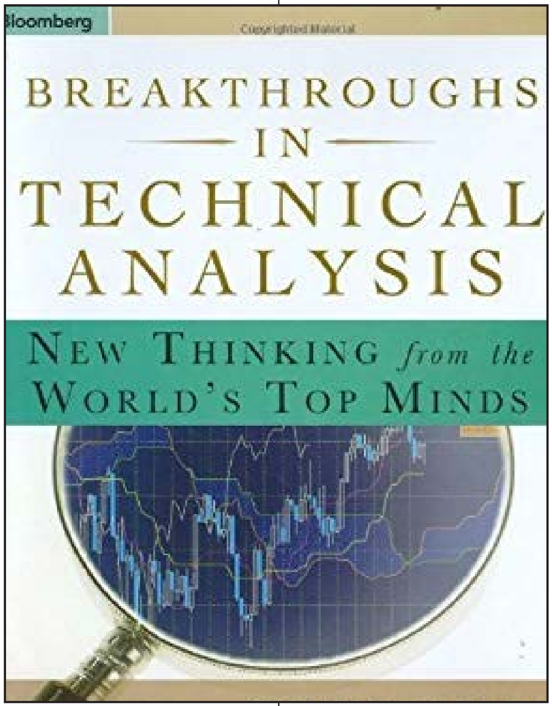
Reviewed by Regina Meani, CFTe

While browsing my technical analysis bookshelves, I came across David Keller's *Breakthroughs in Technical Analysis: New Thinking From the World's Top Minds.* In his introduction, there is a line that I believe is the perennial debate that involves all of us:

Does technical analysis work because people use it, or do people use it because it works?[i]

This book reminds me of the *Market Wizard* tomes written by Jack Swagger. Both Swagger and Keller give us a glimpse into the great minds of technical analysis.

In chapter one, Ted Hearne explains the Drummond Geometry, which builds on some of the basic concepts of technical analysis: support and resistance, the state of the market, and multiple time period analysis—combining them in such a way to produce a methodology for evaluating markets. Most interesting is the use of the Drummond Dot and accompanying envelop system, which can be a useful measure of recent strength and the current energy of the market.



In chapter three, Nicole Elliott explains the advantages of candle charts, which she defines as three things: *speed, speed, speed.*[ii] Elliott takes us through the basics of candlesticks and then into the Cloud. She provides a step-by-step plan of how the charts are set up and how they work. The chapter is a worthy starter for those unfamiliar but curious about this time-honoured Japanese style.

Chapter eight deals with point and figure analysis, and Jeremy Du Plessis points out the changes that occurred in its first 100 years and discusses various interpretations of what he calls *this veteran strategy.*[iii] Du Plessis runs through the construction of these charts, the determination of box size, and the differences using arithmetic and log scaling, and delves into the use of indicators. He also discusses flipping the charts, which is a great way to remove any bias one may have. In this style of chart, one of the main benefits is that it is not restricted by time and therefore is more easily adaptable then other charting methods.

Keller rounds off his admirable gathering of minds with the Ten Commandments from Robin Griffiths. Griffiths confesses that none of them are original to him. The first is attributed to Warren Buffett: *Thou shalt not lose any money, as the probability is too high that you will never get it back again.*[iv] A personal favourite is number 5: *If you hold a position that is going wrong, cut it. At all times for all positions have a clearly identified level for exiting.*[v]

The set of 10 are sensible rules for any trader or investor. It is perhaps appropriate that in this final chapter, we look at an approach that integrates technical and fundamental analysis. *Concepts of value are just as relevant as those of price.*[vi]

The fundamental interpretations rely heavily on economic cycles and annual seasonal deviations. Technically, using a ranking methodology, the long-term trend is sought by calculating the rate of the rise by using a 200-day moving average the short-term trend by a 25-day moving average, and doing the same for the 70-day moving average of the relative strength to the benchmark. Griffiths sets out how to implement this system. He then suggests that for our entry and exit trading rules, we use the tried and true indicators easily at our disposal and do not re-invent the wheel.

Having only touched on a few chapters, I hope that I have inspired you to read or re-read this exploration of technical analysis through the minds of some of the most notable and respected in their field. A reoccurring message throughout the book and succinctly stated in Nicole Elliott's concluding advice: *The more confident you grow with any new technique, the more likely you are to tinker with it. Confidence begets creativity.*[vii]

Notes

[i] D Keller, Breakthroughs in Technical Analysis, New Thinking from the World's Top Minds, Bloomberg Press New York, NY 2007, p. xiii

[ii] ibid, p. 35

[iii] ibid, p. 157

[iv] ibid, p. 205

[v] ibid, p. 205

[vi] ibid, p. 207

[vii] ibid, p. 50

Author Profiles

Min Deng

Min Deng has 25 years of experience in the Chinese stock markets, along with 20 years of hands-on expertise in the international financial futures markets. By relying on such experience and on the significant breakthrough achievements accomplished on the actual investor behavior and stock price behavior, he is capable of making his independent judgment on whether the mainstream financial investment theories are scientific in nature or not. His two representative research papers, titled "Death of the EMH" and "Death of the CAPM," which were accepted for presentation at leading financial conferences, successfully drew the attention of the financial academic circles and financial investment management circles.

He once managed two investment service companies and was in charge of a large research project of developing global financial futures trading systems involving a total cost of more than $1 million spanning over 10 years. Currently, he is providing customized investment consultancy service to a large, private financial investment group in China and several wealthy Chinese families abroad. At the same time, he is acting as the China representative of one of the biggest names in Wall Street dealing with B share trading in the Chinese stock markets.

Akram El Sherbini, MFTA, CFTe, CETA

Akram El Sherbini, MFTA, CFTe, CETA, holds a B.Sc. in physics from the American University in Cairo. He has been involved in financial markets since 2007. Prior to freelancing, he was a technical analyst at Synergy Capital Markets and a team leader at Candle Egypt. His focus is on creating new technical indicators as well as developing unified trading systems for equity and FX markets. Akram is also a member in the Egyptian Society of Technical Analysts (ESTA).

Bharat Jhunjhunwala, CMT, CFTe, MSTA, MFTA

Bharat Jhunjhunwala, CMT, CFTe, MSTA, MFTA, ATA, is a successful technical market strategist with a proven ability to generate actionable investment and trading ideas within the global equity, commodity, and foreign exchange markets. His current focus is the India and U.S. equity markets. His specialties include technical analysis, education and training in technical analysis, and building indicators and screens combining technical data.

Bharat has worked with leading analyst and brokerage firms around the globe, using RSI and Elliott Wave as the backbone of all analyses and strategies. He built the Bytrender Indicator and has assisted and coached hundreds of traders around the country. Connect with Bharat at www.wavemetric.com.

Christian Lundström, Ph.Lic.

Christian Lundström received his B.S., M.S., and Ph.Lic. degrees in economics from Umeå University, Sweden, in 2005, 2006, and 2017, respectively. As a researcher, he is the author of numerous peer-reviewed papers related to investing, technical trading strategies, and money management. He also has a strong background as an investor in all major asset classes from his previous employment as fund manager at Carnegie Investment Bank, senior advisor in manager selection at Folksam, and chief investment officer at Independent Investment Group, Sweden. Currently, he is working as a senior economist/policy advisor at the Financial Markets Department, Ministry of Finance, Sweden. Regulatory work includes suggesting new investment fund and alternative investment fund regulation and suggesting new asset allocation limits for the Swedish pension fund mandates (+Trillion SEK).

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.

Miyoko Nakashima, MBA, MFTA

From 2003 to 2015, Miyoko Nakashima, MBA, MFTA, worked for one of Japan's leading commodity brokers as branch manager, trainer, stock futures broker, and technical analyst and strategist. She also contributed to the company's Diversity Project to make it easier for female employees to continue working after giving birth. During this period, she also found time to earn an MBA at Tama Graduate School of Business and to raise her two young children. In 2014, she joined the company's Investment Research Division as a technical analyst and strategist. She became the first woman to be awarded IFTA's John Brooks Award in 2015. Since joining Mizuho in 2016, she has presented over 100 technical and macro-economic seminars to potential customers throughout Japan annually. She was recently promoted to senior technical analyst. She also provides commentary regularly for Nikkei CNBC and TOKYO FM, and occasionally for Tokyo MX TV, BS Japan, Nikkei newspapers, and other information providers. As an NTAA member, Miyoko has played roles of executive officer of international planning, councilor, and coordinator.

Oliver Reiss, Ph.D., CFTe, MFTA

Dr. Oliver Reiss, CFTe, MFTA, received a master's degree in physics from the University of Osnabrueck (1998) and a Ph.D. in mathematics from the University of Kaiserslautern (2003)—the latter for his research on financial mathematics performed at the Weierstrass Institute in Berlin. Since then, he has worked in the banking industry and today is a self-employed consultant for financial institutions, with a focus on risk controlling, derivatives pricing (quant), and the related IT implementations.

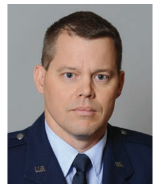
As a private investor, Oliver was interested in technical analysis and joined the VTAD when he became a freelancer in 2011. Currently, Oliver serves as deputy manager of the VTAD's regional group in Dusseldorf and is a frequent attendee of IFTA's conferences. Due to his mathematical and programming expertise, he is focused on the developing and backtesting mid-term trading strategies.

In his MFTA research paper, Oliver presents a good introduction into the Empirical Mode Decomposition (EMD), which is designed to identify cycles with changing amplitude or wavelength. To use this technique on financial time series, Oliver improved the EMD algorithm to increase the stability on the right-hand end of the data. Furthermore, he presents three applications of the EMD. At first, a new kind of moving average is introduced, which is adapted to the obtained cycles. Second, a projection technique is provided, which is based on the idea to continue the identified cycles by damped oscillations. And finally, two profitable trading strategies based on the EMD are introduced and backtested.

Troy J. Siemers, Ph.D.

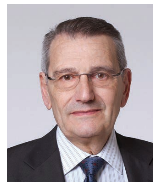
Troy Siemers, Ph.D., is the department head of the Applied Mathematics department at the Virginia Military Institute. He has a broad interest in mathematics and science and has been a co-author on papers in economics, physics, chemistry, and mathematics. He enjoys teaching a range of mathematics courses as well as classes in Matlab programming. For fun, he juggles and runs marathons and ultramarathons.

Jeffrey S. Smith, Ph.D.



Jeffrey S. Smith, Ph.D., is currently an associate professor of economics and finance at the Virginia Military Institute. He is retired from the U.S. Air Force, and he has published in various economics and finance journals. For fun, he enjoys cycling and sailing.

Alberto Vivanti, MFTA



Since the early 1980s, Alberto Vivanti, MFTA, has been a technical and quantitative analyst as well as an asset manager with Swiss institutions. His work is a technical/quantitative approach to investing through the application of proprietary, momentum-based allocation models, with a focus on sector investing through relative strength techniques. In his MFTA research paper, Alberto describes different possibilities to trade sectors in a portfolio-related context.

Alberto is vice president of the Swiss Association of Market Technicians (SAMT). He chaired the 2006 IFTA conference in Lugano, and he was a speaker at the 1998 IFTA conference in Rome, the 2006 conference in Lugano, and the 2017 conference in Milan.

Alberto is an author of technical newsletters, a lecturer at institutions, an organizer and instructor of technical analysis courses in Switzerland for the IFTA certification, an author of articles and books, and a co-author of a book with Perry Kaufman. For many years, Alberto has been a regular contributor to Swiss radio financial news. He contributes regularly to SAMT's Swiss Technical Analysis Journal and other professional publications and websites.

John (Jack) Zippel

Jack Zippel graduated with honors from the Virginia Military Institute in May 2016, majoring in applied mathematics with a minor in business. Driven by a strong interest in analytics and finance, Jack completed various undergraduate research projects and internships, including a project using the predictive capabilities of artificial neural networks to value a set of exchange traded funds. Since graduation, Jack has been working in the risk advisory practice of Ernst & Young, LLP in Richmond, Virginia. He performs a variety of risk management consultancies for clients in the financial services, pharmaceutical, and consumer products industries.

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