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"You can't put a limit on anything. The more you dream, the farther you get."

—Michael Phelps

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Letter From the Editor

By Dr. Rolf Wetzer, CFTe, MFTA

Dear IFTA colleagues

2024 is an unusual year for IFTA in many ways. For the first time in our history, we have published two issues of the *Journal.*

I would therefore like to thank everyone who made this possible. First and foremost, of course, are the authors. This year, we have a colorful mix of articles from colleagues, MFTA papers, an educational section from Italy, and our book review from Australia. Many thanks again this year to the NAAIM and Susan Truesdale, who has allowed us to publish articles from her own collection for many years. In this issue, this is the contribution of Rob Hanna, winner of the NAAIM Founders Award. A major contribution to the production of the Journal comes from Linda Bernetich's production team. Year after year, they produce a publication with quality that never fails to impress. Finally, I would like to thank Regina Meani and Mohamed El Saiid for their input in our team.

Our conference will take place this year from October 4th to October 6th in China, organized by CIDTAA. As always, you can learn something new, catch up with old friends or make new ones, or simply enjoy the venue.

It is not a novelty, but it is still unusual for our conference to be hosted by a developing society from the IFTA family. The last time this happened was 13 years ago in Sarajevo. I would also like to point out that the first IFTA event in China also took place in 2011. At that time, President Adam Sorab organized a congress in Beijing in cooperation with official Chinese authorities. At that time, the entire CFTe Syllabus was presented in compact form by IFTA experts. This was reported in detail in the two IFTA Updates, 2011 Vol. 18, **Issues 2 and 3**. Here is a reminder of the event.

Photo: Mr. Xu Yibing, Executive Vice President, Ms. Rong Rong, Executive Chief Editor and Ms. Sissy Zhang, Vice Secretary-general of SAFE China FX Magazine with some of the speakers.

I hope you enjoy reading the *Journal* and look forward to the many small discussions that regularly arise from this publication.

Best regards,
Dr. Rolf Wetzer, CFTe, MFTA

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Linton Price Targets

A groundbreaking new way of projecting price targets and when they will be met in the future.

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Point and figure charts have largely fallen out of favour in recent decades with the birth of personal computing and electronic data services. Few software systems calculate them correctly, and the technique is seen as outdated and difficult for the newcomer to technical analysis to understand. Linton Price Targets takes the point and figure methodology for producing vertical count targets and applies them to time-based charts that are much more widely used for technical analysis.

History

Point and figure charts were devised over 100 years ago as a necessary shorthand for manually recording prices as they emerged on a ticker tape. Drawing real time price charts by hand for the most heavily traded stocks proved too difficult, so the point and figure method of only recording prices above or below round levels was born. If prices did not change outside the 'box' on the grid, the point and figure chart did not change. When prices moved in line with the direction of previous recorded prices, a new cross would be drawn in the next box in that column. If the trend in prices changed direction, the price would be recorded in that box in the next column to the right. These charts became known as 1-box point and figure charts.

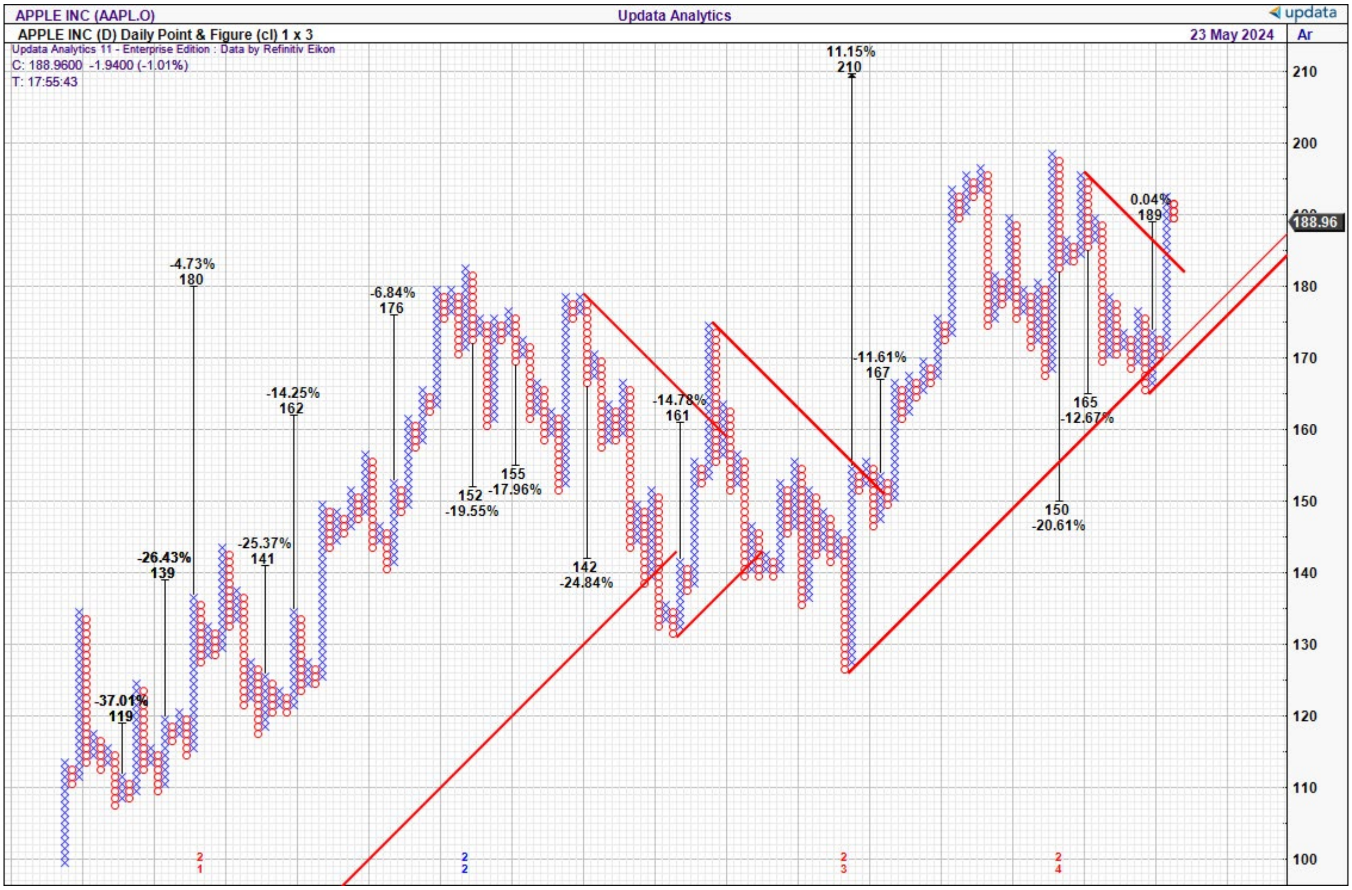
In 1947, A. W. Cohen published his book on the Three-Point Reversal Method of Point and Figure. This provided further filtering by introducing an asymmetrical filter whereby prices had to reverse by at least three boxes in order to move to the next column. This new 3-box method introduced the idea of drawing 'X's for a column of rising prices and 'O's for a column of falling prices, which could be further differentiated with different colours. This chart construction means the x-axis of a point and figure chart is not time, but instead column reversals.

Cohen also introduced the idea of 45-degree trend lines drawn from column high and low points as well as unambiguous buy and sell signals If a column moved one X above the top of the previous column of X's this was a breakout signal called a Double Top Buy (not to be confused with a standard double top pattern that we normally know as a reversal pattern in technical analysis). A move of one O below the bottom the previous column of O's is a Double Bottom Sell. These objective Buy and Sell signals, being less sensitive than normal (and often only temporary) breaks of resistance and support, provided traders with more reliable entry and exit points for trades.

Cohen also devised two methods, the Horizonal Count and the Vertical Count, for projecting price objectives from these new 3-box charts. The upside Vertical Count takes the length of the thrust off a low (number of X's) and projects an upside price target of twice that thrust from the top of the column. The target is said to be activated with the Double Top Buy signal on the next X column. The downside Vertical Count takes the length of the thrust off a high (number of O's) and projects a downside price target of twice that thrust from the bottom of the column. Here, the target is activated with the Double Bottom Sell signal on the next O column.

Figure 1 shows how this rules-based approach appears on a typical 3-box point and figure chart. This is a daily $1 x 3-box chart whereby the box size unit is $1. The sensitivity of the chart can be increased by making the box size smaller (say a 50c box) and by using intra-day price points. The original point and figure charts were constructed with every price tick. This level of a long tick price history may not be readily available today, such that one minute, hourly or daily data may be used.

Figure 1: 3-Box point and figure chart of Apple, Inc.



The Problem with Point and Figure Charts Today

Point and figure charts slowly fell out of favour with the birth of modern computing and telecommunications. The need for this shorthand method of recording price information was superseded with the technological ability to store and retrieve large volumes of real-time and historical price data. Point and figure charts are also hard to computerise and very few software systems are able to produce them on a computer screen properly. For the newcomer, point and figure is hard to understand and does not appear to offer additional value to other technical analysis techniques.

One of the biggest advantages of point and figure charts is the ability to project vertical price objectives. But because there is no time axis on a Point and figure chart, there is no way of knowing when a vertical price objective may be reached. Point and figure price targets have no time scale. The idea that Linton Price targets seeks to address is this main shortcoming by placing point and figure style price targets on time-based charts and projecting them into the future.

Deconstructing Point and Figure to a Time-Based Chart

To place Point and figure price targets on a time-based chart, we first need to relate the conditions that produce the vertical count targets. Figure 2(a) shows a typical Point and figure Double Top Buy pattern with a vertical upside target generated from a low point in price. A price low in point and figure terms is where the base of the column of O's is lower than the previous column of O's. Figure 2(b) shows a schematic diagram of how the pattern in Figure 2(a) might appear on a time-based line chart. Figure 2(c) shows how a point and figure Double Bottom Sell pattern may look as a line chart.

Figure 2: How point and figure patterns might look in simple line chart form.

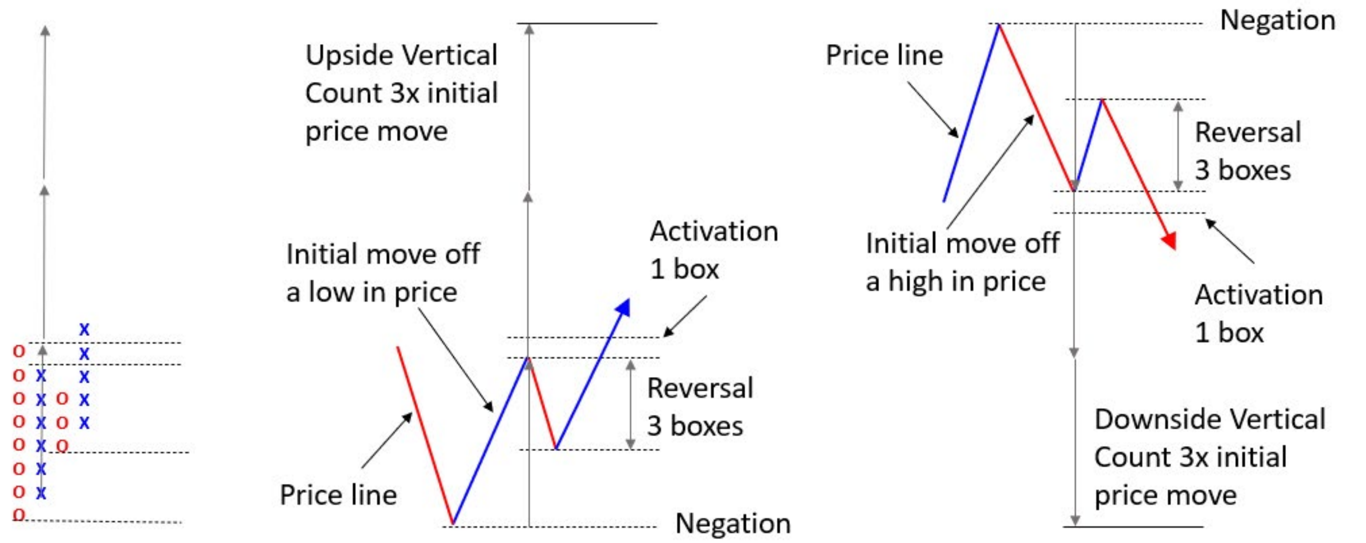


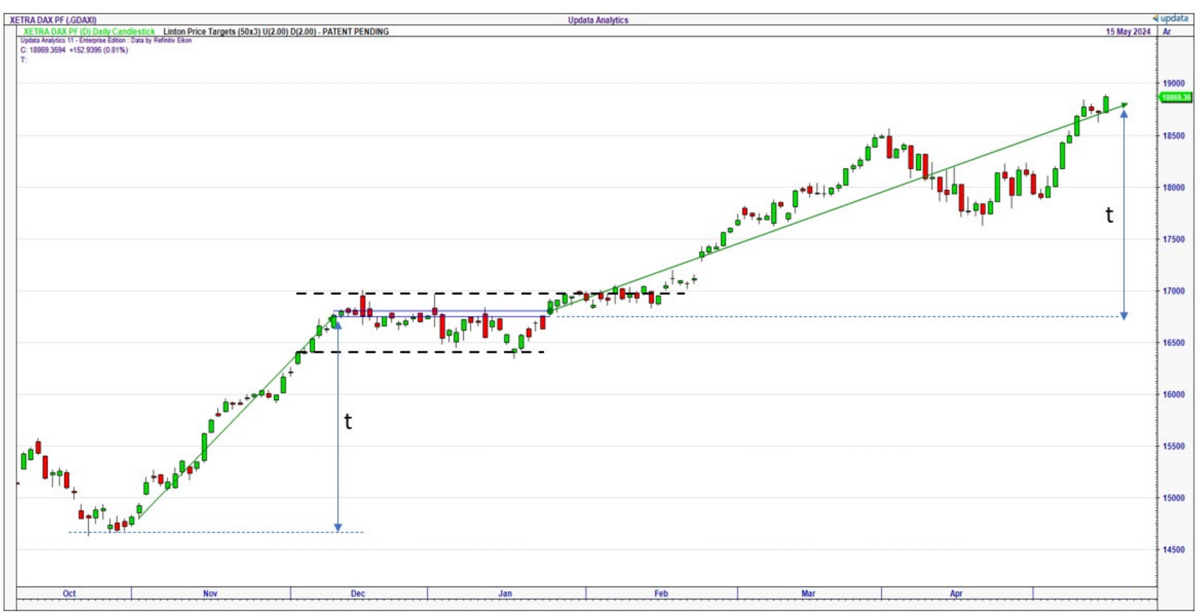
Figure 2 (a) Figure 2 (b) Figure 2 (c)

Vertical Targets are only generated with uninterrupted moves off a high or a low point in prices. A pullback of at least 3 boxes locks the thrust column and therefore the price target. A move of at least one box above (in the case of an upside target off a low) or one box below (downside off a high) 'activates' the price target. Here the buyers and sellers respectively are confirmed. Conversely a move below the base of an upside target column, or above the top of a downside column 'negates' the vertical target. In this case, the buyers and sellers have been superseded by subsequent events.

Projecting Price

The price projection following the point and figure 3-Box method is relatively straightforward. The standard projection used is twice the original move from the top of the initial thrust level. This derives from the 3-Box construction devised by Cohen, whereby the initial thrust count is a third of the overall price count projection. But there is no reason to limit the Target Price Factor to the value to 2. A value of 1 could be used in the case of consolidation patten where the move out of the pattern is roughly equivalent to the move into the pattern. A value of 1.618 could be used for Fibonacci Retracements or Extensions or a value of 2 x log, can be used to deal with increasing box (unit) sizes as price changes. Figure 3 shows an example of a target factor of 1.0 on the DAX Index.

Figure 3: Using a target projection factor of 1 for the move into and out of a consolidation phase in prices.



Projecting Time

Projecting a potential price target with is relatively straight forward. Determining a time in the future when such a price target will be met is more of a challenge. This has been seen as one of the major drawbacks of point and figure charts for decades. Because there is no time axis on a Point and figure chart, there is no saying when a count projection target will be met.

Figure 4: The key elements for Price Target construction.

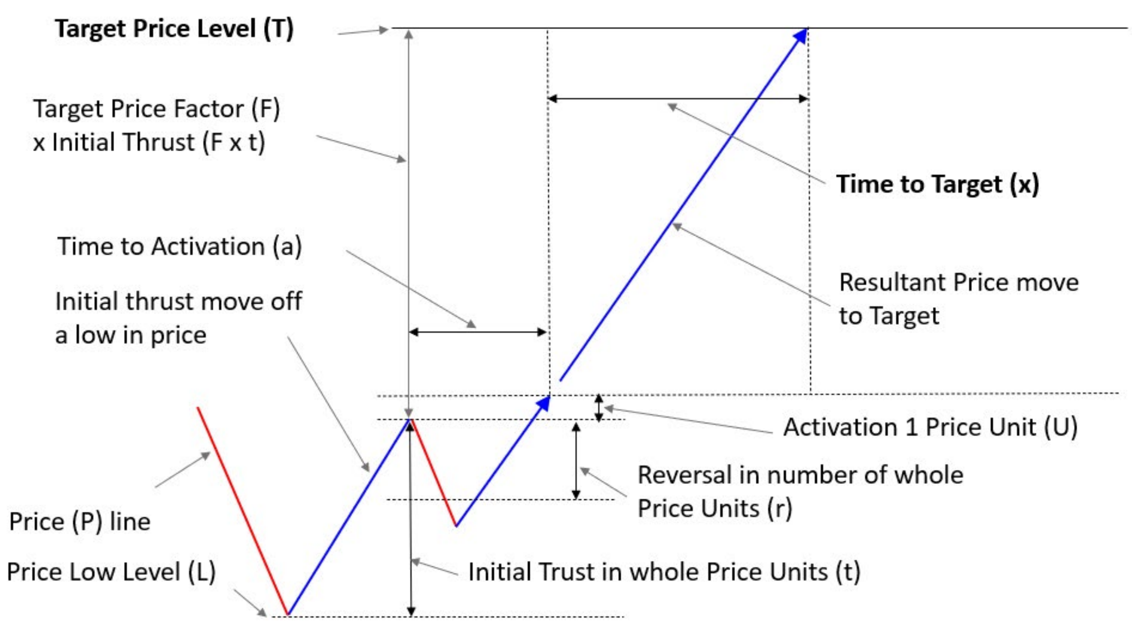


Figure 4 shows the key elements for predicting future prices. The Target Price Level is purely formulaic. For the Time to Target, we need to consider potential methodologies such as:

1. Price to Time Ratio – t units of price for every x units of time – ie $1 every 2 days
2. Thrust Angle Factor – a factor x the initial trust angle for the target angle
3. Time to Activation Factor – time to target is x the time taken for a target to activate
4. Follow the Price – track prices as the progress to target and adjust time to target accordingly
5. Historical Average Slope – historical average price time average for last n targets

Considering the Price to Time Ratio method, Figure 5 shows a chart of the price targets for the US stock Applied Materials with a Unit size of $1. The targets are projected Log Scale 2x the initial thrust. From this chart we see that the target prices are reached later than the projection predicted. This means that we need to consider a lesser slope. Figure 6 shows the same chart with the slope now adjusted to $1 every three days. This chart shows that recent targets for Applied Materials have been approximately met with this slope. Therefore, this is a better slope to use in this instance.

Figure 5: Applied Materials with price targets with a unit size $1 — target projection slope $1 every two days.

Figure 6: Applied Materials with Price targets with a unit size $1 — target projection slope $1 every three days.

Figure 7: Applied Materials (unit size $1) — target projection slope 1/2 initial thrust slope.

The second method of projecting price targets assumes the time that a price target will be reached is directly related to the speed of the initial thrust, which generates the target. Figure 7 shows the same security as in the previous examples but using this method with an angle of slope which is half the initial thrust angle. The factor can also be altered with this method to best fit the data. In the previous examples (Figures 5 & 6) we see the slope of each of the targets is constant. Using the Thrust Angle Factor method, different buying and selling thrust angles produces different target slopes.

A third possible projection method assumes that the longer a price target takes to activate, the longer it takes for a target to be reached. The argument goes that the pullback from the initial thrust is more of a consolidation phase rather than a sharp reaction and therefore, the potential overall move will take longer. Figure 8 shows this method. Again, we see that, due to the varying times of price targets to activate, the slopes of the targets are not uniform as in Method 1 which uses a consistent price to time slope.

Figure 8: Applied Materials (unit size $1) — target projection x times the time taken for target to activate.

Figure 9: Applied Materials (unit size $1) — target projection readjusts with new price information.

A fourth method for predicting when in the future that a price target might be met adjusts the slope of the targets from the activation point as new price information arrives. With multiple targets activated at different points on the chart, this method also produces price targets of different slopes. Because targets are readjusted with every new price, it is best to set this method to ignore the last x bars in order to spot any divergence from the targets. Figure 9 shows this methodology.

Figure 10 shows a method where the average slope of price over time is taken for the previous n targets that are achieved and used as the slope for projecting targets into the future. While the slopes for upward and downward targets can be separately adjusted with the previous methods mentioned, this method automatically calculates the different slope speeds of upside and downside targets.

Figure 10: Applied Materials (unit size $1) — target projection based on the average slope of the last x targets.

Multiple Price Targets

As with Point and figure count targets, multiple price targets point to the same price or price level increases the likelihood of price targets being met. This is known as ‘clustering’. Now with the ability to project price targets to a future date on a chart, it is not only possible to see clustering of the price of multiple targets, but also clustering of times targets may be met. This can lead to a ‘cluster zone’, an area of price and time in the future that multiple targets may be met. Figure 11 shows an example of this.

Figure 11: Applied Materials (unit size $1) — target zone of future price and time of multiple targets.

Achievement and Non-Achievement of Price Targets and Prevailing Trend

Point and figure targets are approximate and are more often than not, not met precisely. They are regularly not achieved or exceeded, but this provides valuable information in itself. Upside price targets that are achieved or exceeded shows bullish confirmation, whereas these targets not being achieved indicates a degree of bearishness. Conversely, downside price targets achieved or exceeded is bearish confirmation and such targets not achieved is an indication of inherent bullishness.

Unsurprisingly, price targets are normally achieved or exceeded in line with the prevailing trend. Upside price targets should be given more weight in uptrends, while downside ones may only serve as a temporary moment for caution, because they are counter-trend. Downside Targets will carry more weight in downtrends. It is also often the case that the last target in line with the prevailing trend is never met as the trend changes and a new set of targets in the opposite direction are generated with the new reversal of trend. Active price targets in both directions areoften an early sign of this. This is particularly true with multiple targets in the new trend direction verses one lone target in the previous trend direction. This lone target is likely to be negated, clearly signalling the new trend direction is taking hold.

Activation and Negation of Price Targets

An upside price target is only activated when prices rise a further than a full price unit above the top of the initial uninterrupted buying thrust in prices from a low. A low is defined by a price level at least one full price unit below a previous recent low. The pullback downwards of at least three price units ‘locks’ the initial thrust that generates the upside price target. Here the bulls buying from the bottom have been confirmed.

A downside price target is only activated when prices fall further than a full price unit below the bottom of the initial uninterrupted selling thrust in prices from a high. A high is defined by a price level at least one full price unit above a previous recent high. The pullback upwards of at least three price units ‘locks’ the initial thrust that generates the downside price target. Here the bears selling from the top have been confirmed.

A target is valid once the column is locked with the pullback of at least three units, but it should not be considered as active until the price breaks through the activation level. An unactivated target serves as advance notice that a target is in place and will become active once the activation price level is broken.

An upside price target is negated if prices fall below the bottom of the initial uninterrupted buying thrust in prices. In this instance the bulls have been beaten by the bears. Conversely, a downside price target is negated if prices rise above the top of the initial uninterrupted Selling thrust in prices. Here the bears selling from the top have been beaten by the bulls.

It is important to note the difference between a target that is activated first and then negated and a target that was never activated and negated first. Research shows that normally more than half of all negated targets were never activated and wouldn't have been taken. Taking the prevailing trend into account further reduces the number of negated targets that would have been taken at the activation point. Figure 12 shows the difference between targets activated then negated and not activated and then negated.

Figure 12: Showing 11 targets activated then negated versus 13 negated never activated.

Evaluating a Target as Price Progress

Because Linton Price targets can be evaluated with subsequent new price information with the passage of time, it becomes possible to see more easily, than on a point and figure chart, when a target might be failing. The ideas of activation, negation, and achievement of price targets are understood in point and figure charting and apply similarly here to time-based charts. But the ability to now see prices diverging from the target path presents us with some potential new states of a target.

In the case of an upside target, if prices fall away or wander sideways from a target path this alerts us to the fact that the prices on their way to the target may be 'exhausting'. If we fall or wander back below the target activation level, this implies the previous resistance level off the thrust high has not managed to become a new support level for the price. Consequently, we may consider that the target has been 'de-activated'. If we fall further below the low of the pullback low point, this previous support level also failed to hold and this is providing us with an early warning that the target is quite possibly 'failing.' If prices are moving towards the target as expected, we can say the target is 'in train.' This is particularly appropriate for multiple targets that run parallel using the first price/time slope prediction method where the targets look like 'train tracks.' Figure 13 shows these target states for an upside price target and Figure 14 shows them for the reverse case of a downside price target.

Figure 13: Target states for an upside price target.

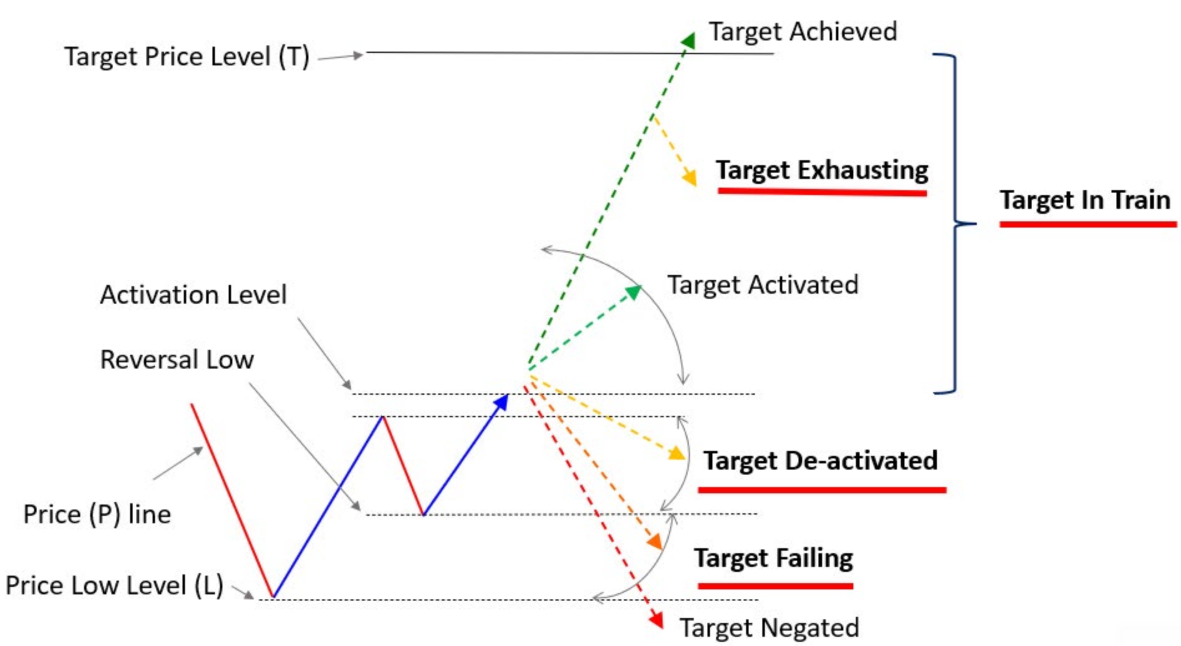
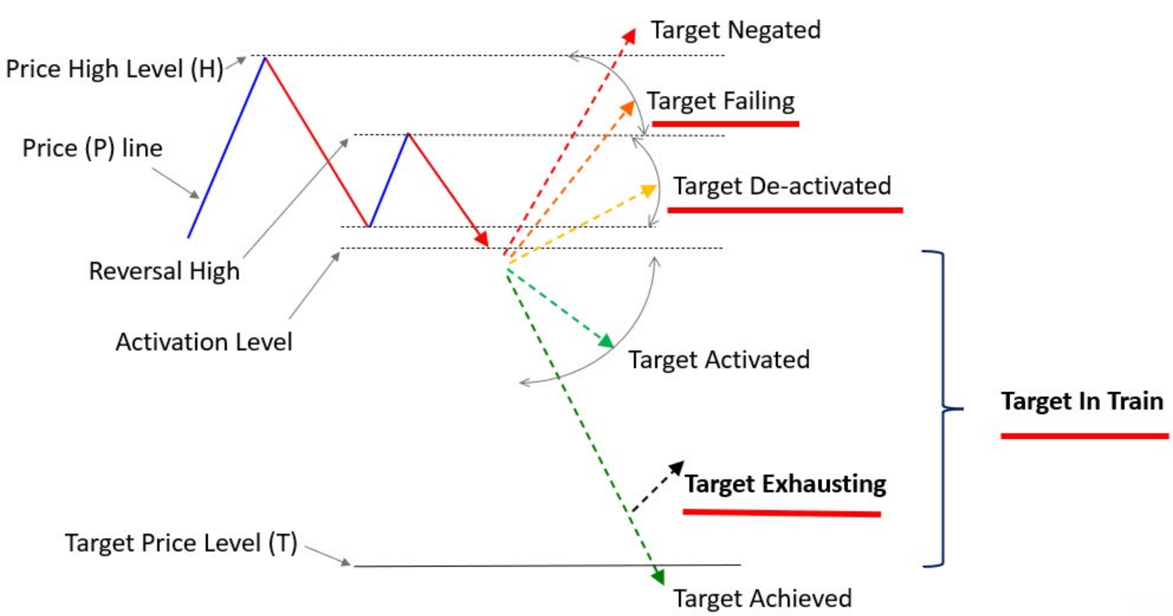


Figure 14: Target states for a downside price target.



Improprobable Targets

Occasionally an improbable target a long way from the price will be generated. This is particularly true using a log scale projection. Beware of a target that points to a very large change in price. This is especially true of a lone target. It is also quite likely that the unit size has been set too small where a bigger unit size may not produce a target at all. Figure 15a shows an improbable target and a check of the point and figure chart for the same instrument with matching unit and box sizes, 15b, shows the box size used is much too small.

Figure 15a: Example of an improbable Target.

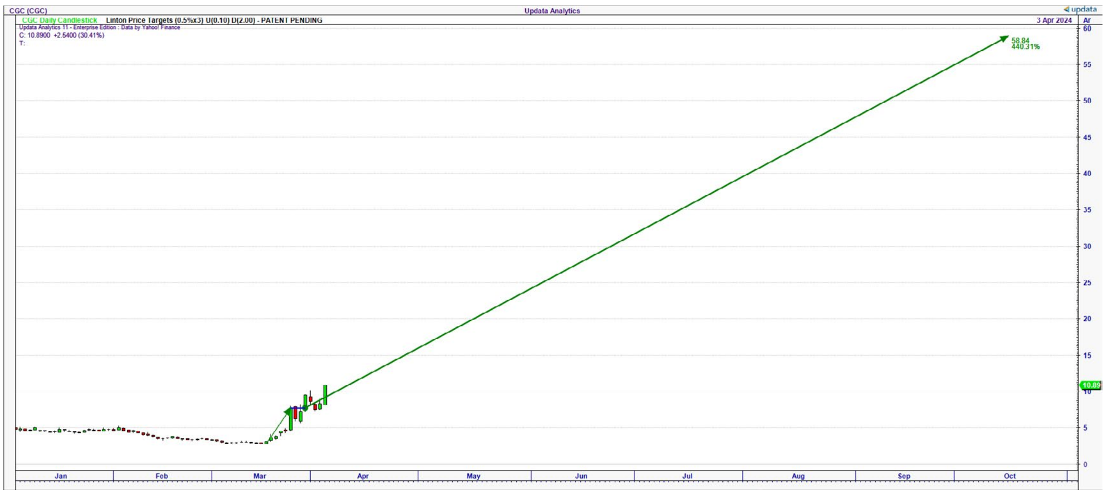
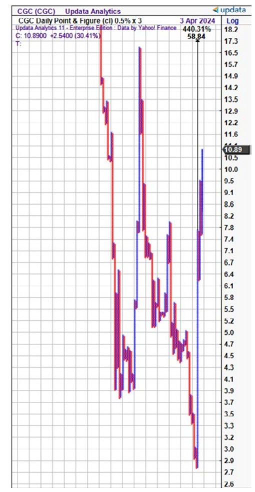


Figure 15b.



Longer term charts

Point and figure charts have always meant to be constructed with tick data. The point and figure methodology reduces this down to just the ticks that create a new box on the chart. Long tick data price histories are typically expensive and hard to come by. This can also be an overwhelming amount data to store and analyse, particularly in the case of very liquid instruments such as a major currency pair. For intraday charts, one minute data will normally suffice. But these histories may not be long enough either and it may be necessary to use a 60-minute chart.

It is also possible to construct point and figure charts using high/low data or even open-high-low-close data making some assumptions based on a rising or falling candle, on which came first, the high or the low. The targets will be impacted accordingly.

When it comes to longer term charts such as weekly or monthly charts it is unlikely that these time frames would be used for point and figure charts. The construction method already filters the data. But when it comes to long-term time-based charts it becomes necessary to look at weekly or monthly data. Figure 16 shows a daily point and figure chart of gold over the past ten years on the left. The chart on the right is a monthly chart of gold over the past ten years. Here a daily chart would be very noisy with thirty times more data points. Monthly time series analysis can also be applied, in this case an Ichimoku cloud chart.

We also see in Figure 16 that long term price upside targets are generated that are not on the daily chart. This is because daily the movements will not provide the same uninterrupted buying thrusts as with the monthly data. The daily pullbacks are effectively ignored when using monthly data. The other advantage is the unit size is now months so we can say that the target slope equates to 1% of price every month for a 1 to 1 slope for example. Using weekly or monthly data to construct the price targets is a significant departure from the traditional point and figure charting method.

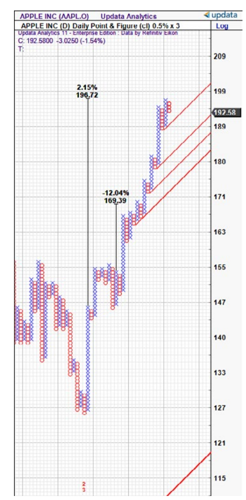
Figure 16: Daily point and figure chart of gold and a monthly Ichimoku chart with price targets.

Time-Based Charts Are Easier to Understand Than Point and Figure Charts

In recent years, the vast majority of people carrying out technical analysis of charts do not use the point and figure charts. This is partly because very few software systems draw them correctly and do not calculate the price targets. Newcomers to technical analysis find point and figure charts hard to understand. Figure 17a shows the Linton Price Target for Apple, Inc. and Figure 17b shows the corresponding point and figure chart. Most technical analysts would prefer the first chart over the second.

Figure 17a: Linton Price Target for Apple, Inc.

Figure 17b.



Combining With Other Techniques

Using point and figure charts has also often meant the need to switch between different chart types for the same instrument. Time-based charts allow for a vast set of technical analysis time-series based techniques to be married with Linton Price Targets. For instance, Figure 18 shows a 60-minute chart of silver with Bollinger Bands and the price targets on the same chart. Having different sets of analysis on the same chart can increase the power of the analysis without having to swap between different chart types.

Figure 18: Bollinger Bands with Linton Price targets for 60-minute chart of silver.

Conclusion

Linton Price Targets builds on the technical analysis body of knowledge developed over the past 100 years by bringing an old, largely lost, technique into the modern age.

The main advantages of Linton Price Targets are:

- The ability to have price targets on time-based charts.
- It is now possible to ascertain when in the future a price target may be met.
- With the passage of time, it becomes clearer if a target track is being followed.
- The targets can be applied to longer-term time-based charts.
- Time-series based analysis techniques can be used on the same chart as the targets.
- The targets are much easier to understand for the newcomer to technical analysis.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Prediction is Very Difficult: Especially if It's About the Financial Markets!

A rigorous evaluation of statistical forecasting methods and their comparative effectiveness.

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"... Prediction is very difficult, especially if it's about the future! ..."
Niels Bohr (1885-1962), Danish physicist, Nobel Prize in Physics (1922)

1. Introduction to the First Part

In the ever-evolving landscape of financial markets, accurately forecasting asset prices and market trends remains a critical challenge for analysts, traders, and investors. This comprehensive essay, now divided into four parts, presents a detailed exploration of statistical forecasting methods, rigorously evaluating their effectiveness and comparative advantages in the financial sector. This first part introduces fundamental concepts of forecasting models, providing a general introduction to those models and their components, describing the financial asset and time series data utilized, and explaining the segmentation of the historical backtesting period into training and testing ranges. It also discusses model selection criteria and accuracy metrics and introduces simple forecasting methods as a baseline for understanding more sophisticated techniques.

This initial focus on simple forecasting methods sets the stage for understanding more complex models, making it crucial for financial technical analysis as it lays the groundwork for accurate and reliable predictions, essential for informed decision-making in the financial sector. Subsequent parts will delve deeper into more advanced methods. Part Two will explore exponential smoothing methods, offering a comprehensive analysis and discussing procedures for optimal parameter selection. Part Three will focus on ARIMA models and their variants, providing detailed discussions and practical implementations of non-seasonal and seasonal ARIMA models. Finally, Part Four will address advanced forecasting methods, incorporating volatility modeling through GARCH models and tackling the challenges of non-Gaussian financial data.

By beginning with the simple methods analyzed in this paper, readers can build a strong understanding before progressing to more complex models, ensuring a comprehensive and structured exploration of statistical financial forecasting. This segmented approach ensures that each part provides a focused examination of forecasting methods, paving the way for reliable and insightful financial predictions and decisions.

This extensive analysis will be featured in the *IFTA Journal*, starting with Part One in the 2025 issue and continuing with the subsequent parts in following issues. The publication of this work in the leading journal of technical analysis underscores the significance and relevance of these topics to the field of financial forecasting. It aims to reach a broad audience of professionals, practitioners, and academics dedicated to advancing the science of market prediction within the realm of Technical Analysis.

2. Forecasting Models

Forecasting models consist of time series prediction by identifying the trend, seasonal and cyclical patterns in the financial markets [1][2][3]. The trend component in time series forecasting models captures the long-term movement of financial data. In the context of financial markets, this represents the direction in which an asset's price, or a market index, is heading. Identifying and understanding trends is critical for investors and traders as it offers insights into whether a market is in an upward, downward, or sideways trajectory. Seasonality is the recurring fluctuations in financial data driven by calendar-based or periodic effects. These patterns often follow a consistent annual, quarterly, or monthly schedule. For instance, retail stocks may experience increased demand during the holiday season, leading to predictable seasonal spikes in their prices. In finance, identifying and accounting for seasonality is crucial for understanding when certain assets tend to perform better or worse. Cyclical patterns in financial time series data reflect the medium to long-term fluctuations resulting from economic cycles. These cycles encompass periods of economic expansion and contraction, which can last several years. In the financial context, recognizing these cycles helps investors and policymakers navigate volatile markets, adjust strategies, and anticipate market turning points. In this work we will consider only trends and seasonality patterns.

Additive Forecasting Models

Additive models are time series forecasting models used to predict future values of a time series by considering the additive combination of its various components. The observed value y_t can be expressed as:

$$y_t = t_t + s_t + e_t,$$

where the three components are:

1. *Trend Component* t_t: The trend component represents the underlying long-term direction or pattern in the time series data. It accounts for the gradual increase or decrease in values over time;
2. *Seasonal Component* s_t: The seasonal component captures the recurrent, short-term patterns that repeat at regular intervals, such as daily, weekly, monthly, or quarterly. These patterns are often associated with calendar-based or periodic

effects, like holidays or seasonal demand;

3. *Error Component e_t:* The error component, also known as the residual or noise, represents the random fluctuations or unexplained variations in the time series that are not accounted for by either the trend or seasonal components. It is typically assumed to be normally distributed with a mean of zero.

The advantages of additive models can be summarized as follows:

- *Interpretability:* Additive models allow for a clear interpretation of the individual components (trend, seasonality, and error) and their impact on the time series;
- *Ease of Implementation:* These models are relatively straightforward to implement and do not require complex mathematical techniques;
- *Useful for Linear Patterns:* Additive models are well-suited for time series data with linear or additive patterns.

The limitations of additive models are:

- *Not Suitable for Non-Linear Patterns:* When the relationships between the components are not additive, these models may result in poor forecasts;
- *Inadequate for Time-Varying Variance:* Additive models assume constant variance, which may not hold true for time series with changing volatility. In such cases, models like GARCH might be more appropriate;
- *Limited Forecasting Horizon:* Additive models may not perform well when forecasting too far into the future, as they do not account for the compounding effect of the components.

Therefore, additive models can be particularly useful when the impact of these components on the time series is considered additive or linear.

2.2 Multiplicative Forecasting Models

Multiplicative models are time series forecasting models used to predict future values of a time series by considering the multiplicative combination of its various components, as represented by the following expression:

$$y_t = t_t * s_t * e_t.$$

The advantages of the multiplicative models are:

- *Suitable for Non-Linear Patterns:* Multiplicative models are well-suited for time series data with non-linear or multiplicative patterns, where the impact of the components is proportional rather than additive;
- *Accurate for Time-Varying Variance:* These models are better at handling time series with changing variance or volatility, making them useful for financial data, which often exhibits such behavior;
- *Useful for Relative Proportions:* Multiplicative models are appropriate to capture relative proportions or growth rates within the components.

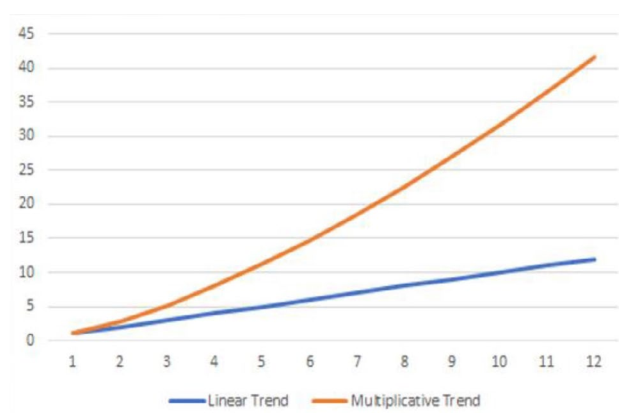
The limitations of the multiplicative models can be summarized as follows:

- *Complex Interpretation:* Multiplicative models may be less straightforward to interpret than additive models, as they involve multiplications rather than additions;
- *Challenging Forecasting:* These models can be more challenging to forecast with, especially when dealing with long forecasting horizons.

The trend component, t_t, and the seasonal component, s_t, are multiplied together, implying that the seasonal effect becomes proportionally larger or smaller as the trend increases or decreases. Multiplicative seasonality is appropriate when the magnitude of the seasonal fluctuations changes with the trend, and it is often used when the seasonal patterns exhibit relative growth or decay over time. In summary, multiplicative forecasting models are valuable for predicting time series data when the trend, seasonality, and error components are believed to have a multiplicative relationship, and they are better suited for non-linear patterns and time-varying variance.

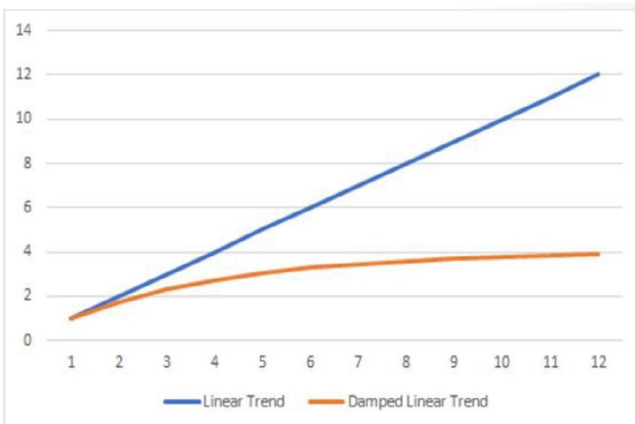
Forecasting model patterns have the following graphical representations. A multiplicative trend occurs when the rate of change in a time series is not constant but instead varies in proportion to the current level of the data, as it is shown in Figure 1.

Figure 1. Liner vs multiplicative trend



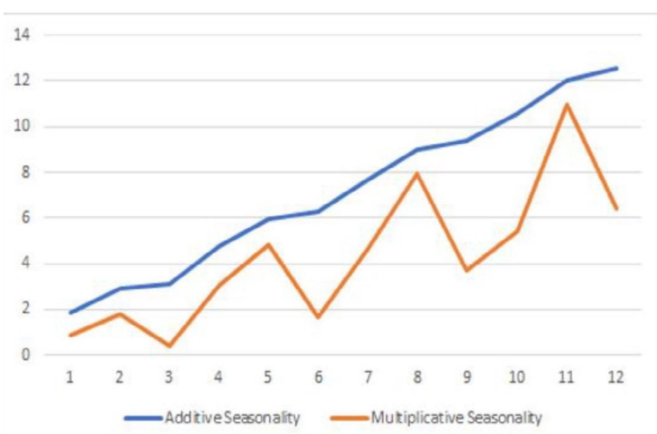
A dampened linear trend combines elements of both linear and multiplicative trends. It represents a linear trend that gradually decreases or dampens over time. In other words, the rate of change is linear, but it diminishes as time progresses, as illustrated in Figure 2.

Figure 2. Linear vs damped trend



In additive seasonality patterns, the seasonal component is added to the overall trend and error components of the time series. This means that the seasonal fluctuations are relatively constant and do not change in proportion to the trend or the level of the data. Additive seasonality is commonly observed when the seasonal effect is fairly consistent from one season to the next. In a multiplicative seasonality pattern, the seasonal component is multiplied by the overall trend and error components of the time series. This means that the seasonal fluctuations are proportional to the trend or the level of the data. Multiplicative seasonality is commonly observed when the seasonal effect grows or shrinks with the overall trend, as shown in Figure 3.

Figure 3. Additive vs multiplicative seasonality



3. Forecasting Models Data

The forecasting models' data used in this work is based on S&P 500 State Street Exchange Traded Fund ETF daily prices (ticker: SPY) spanning a time period of about nineteen business calendar years (from December 1st, 2004, to July 31st, 2023: 4,697 observations). The historical data time series used in this work was downloaded from *Yahoo! Finance* [4]. The "adjusted close prices" have been considered: they refer to a modification made to the closing prices of a financial asset, usually a stock or an index, to account for various corporate actions such as dividends, stock splits, and rights offerings. These adjustments are made to provide a more accurate representation of the asset's value over time and to ensure that historical price data are consistent and comparable. By using the adjusted close prices, financial analysts and investors can accurately analyze the historical performance of a stock over time, even in the presence of corporate actions that might otherwise distort the raw price data. These adjustments help maintain consistency in price trends and facilitate meaningful technical analysis, charting, and performance comparison.

The SPY adjusted close prices time series is divided into a training range for optimal parameters estimation or fine tuning, and a testing range for forecasting accuracy and robustness evaluation. The training range covers 3,424 observations, from December 1st, 2004, to July 9th, 2018, while the testing range includes 1,273 observations, from July 10th, 2018, till July 31st, 2023. The training and testing range charts are shown in Figure 4 and Figure 5 respectively.

Figure 4. SPY ETF training range (Dec 01, 2004 – Jul 09, 2018)

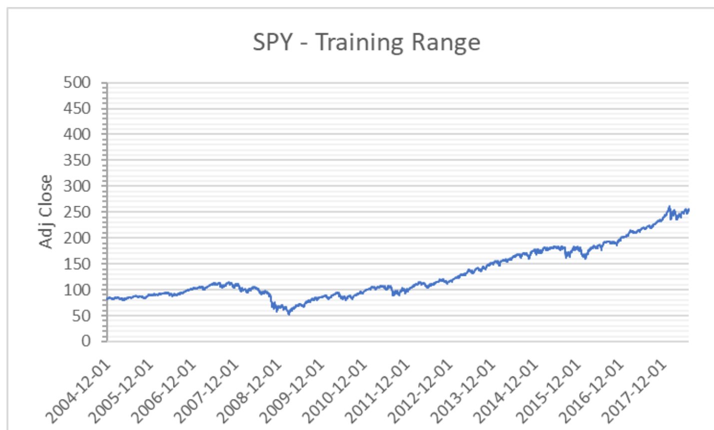
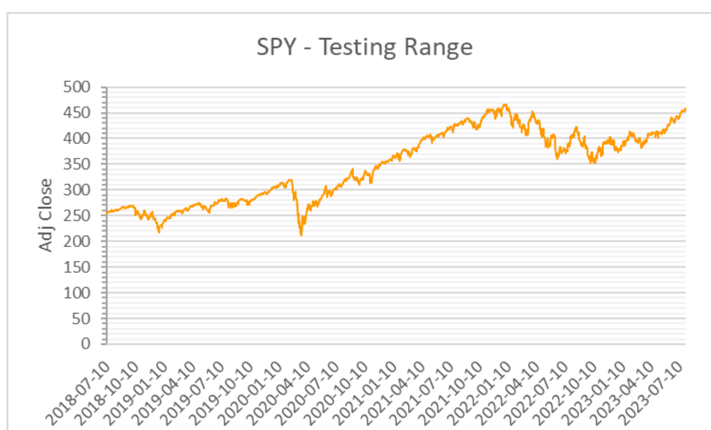


Figure 5. SPY ETF testing range (Jul 10, 2018 – Jul 31, 2023)



The choice of the time window for testing a forecasting model or a trading strategy has always been of interest and concern to the technical analysts to assess its robustness and accuracy, since different periods and sizes of the window can lead to different results and conclusions. The study presented in [6] assessed the robustness of the performance of a strategy given the window size of the backtesting period. This study shows the impact that the chosen window can have on the results and as such, the authors argue that the window should not be arbitrarily selected. In [7] it was demonstrated that an active market timing strategy outperforms the passive buy-and-hold strategy during bear markets and vice versa during bull markets. To account for these results, the study in [7] concluded that the look-back period should include bear and bull markets to observe both these market conditions. Therefore, the forecasting models analyzed in this work were tested across an historical data length covering the past nineteen years (from December 2004 to July 2023), because it includes multiple bull and bear markets, some of which were quite significant, like the global financial crisis (2007-2008) and the more recent COVID-19 sell-off (March 2020), and the last bull market lasting over a decade.

4. Forecasting Accuracy Metrics and Model Selection Criteria

The evaluation of forecasting models becomes pivotal in determining their effectiveness, therefore forecasting accuracy metrics and selection criteria are instrumental not only to assess the effectiveness, but also the robustness of any forecasting model. It is important to note that effectiveness and robustness are crucial when evaluating forecasting techniques, but they address different aspects of a model's performance and behavior:

- Effectiveness refers to how well a forecasting model accurately predicts future outcomes based on historical data. In other words, it assesses the model's ability to generate forecasts that are close to the actual values. A forecasting model is considered effective if it consistently produces accurate predictions over time, minimizing the discrepancy between its forecasts and the actual outcomes. Accuracy metrics such as *Mean Absolute Error* (MAE), *Root Mean Squared Error* (RMSE), *Mean Absolute Percentage Error* (MAPE), and *Mean Absolute Scaled Error* (MASE) are used to measure the effectiveness of a forecasting model. The goal of improving effectiveness is to enhance the precision and reliability of the model's predictions.
- Robustness focuses on the model's ability to maintain its performance across various conditions, including different datasets, changing environments, and unexpected events. A robust forecasting model remains accurate and stable even when facing variations, outliers, noise, or shifts in the underlying data distribution. A robust model does not break down or significantly degrade its performance when subjected to different scenarios or when the underlying assumptions of the model are challenged. For example, a forecasting model that performs well on historical data from the training set, might not be robust if it is applied to data from the testing set with varying characteristics. A robust model can handle such differences and provide reasonably accurate forecasts in various contexts (i.e., on an unknown testing set) and has the capability to generalize to new data.

In this work, to evaluate the accuracy and robustness of the forecasting models, we use the testing set, which is a critical component for assessing not only the accuracy, but also the robustness of a model's predictions.

4.1 Robustness evaluation using the testing set

When evaluating the robustness of a forecasting model, we examine how well the model performs under various challenging conditions, such as changes in data distribution and structure, the presence of outliers, or shifts in the underlying patterns. The testing set, which consists of new and unseen data for the model, provides an ideal platform to assess how the model responds to changing scenarios. By testing the model in diverse situations represented in the testing set, we can determine whether the model's accuracy and performance remain stable or degrade significantly. If the model's performance on the testing set remains consistent across different conditions, it is an indication that the model is robust. Therefore, using the testing set to evaluate robustness is an excellent practice. It helps to ensure that the forecasting model is not just accurate under ideal conditions (i.e., after optimization performed in the training set), but it can also provide reliable predictions in real-world scenarios, where the data might not perfectly match the assumptions made during model's training.

4.2 Accuracy evaluation using the testing set

The accuracy of forecasting models is not a simple binary concept, and it encompasses several measurements highlighting different aspects of performance; thus, it is essential to have a comprehensive understanding of the various accuracy metrics available and their implications. Forecasting models' accuracy is evaluated through scale-dependent and scale-independent metrics. Scale-dependent accuracy metrics are used to assess the accuracy of forecasting models in relation to the actual values of the target variable. These metrics provide insight into how well the model's predictions match the observed data on an absolute scale. On the other hand, scale-independent accuracy metrics are used to assess the accuracy of forecasting models without being influenced by either the scale or magnitude of the data. These metrics provide a relative measure of accuracy that is not tied to the specific values of the target variable. This is particularly useful when comparing the performance of different models on datasets with different scales or units. The scale-dependent and scale-independent accuracy metrics used in this work are:

- *Scale-dependent metrics:* mean absolute error (MAE) and root mean squared error (RMSE);
- *Scale-independent metrics:* mean absolute percentage error (MAPE) and mean absolute scaled error (MASE).

These metrics provide distinct insights into forecasting performance. Choosing the right metric depends on the nature of the data, the goals of the forecast, and the tolerance for different types of errors:

- *Mean absolute error* (MAE) is a scale-dependent measure of forecasting accuracy based on arithmetic mean of absolute value of residuals or forecasting errors:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t|,$$

where the forecasting errors or residuals are expressed as:

$$e_t = y_t - \hat{y}_t.$$

- *Root mean squared error* (RMSE) is a scale-dependent measure of forecasting accuracy based on square root of arithmetic mean of squared residuals or forecasting errors:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}e_t^2}.$$

- *Mean absolute percentage error* (MAPE) is a scale-independent measure of forecasting accuracy based on arithmetic mean of absolute value of residuals or forecasting errors as percentage of actual data:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t} * 100\right|.$$

- *Mean absolute scaled error* (MASE) is a scale-independent measure of forecasting accuracy based on arithmetic mean of absolute forecasting errors or residuals divided by training range random walk or seasonal random walk mean absolute error [5]:

$$MASE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{MAE_{rw}}\right|$$

$$MASE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{MAE_{srw}}\right|.$$

The random walk mean absolute error is equal to:

$$MAE_{rw} = \frac{1}{n-1}\sum_{t=2}^{n}|y_t - y_{t-1}|$$

and the seasonal random walk mean absolute error is equal to:

$$MAE_{srw} = \frac{1}{n-m}\sum_{t=m+1}^{n}|y_t - y_{t-m}|,$$

where m is the corresponding forecasting seasonal lag.[2] The MASE is a scale-independent accuracy metric comparing the forecast errors of a given model to the errors of a simple baseline forecast or benchmark, typically a naive forecast like the random walk. It is also valuable when dealing with intermittent demand patterns or when the data contains outliers. A value of 1 indicates that the model's performance is equivalent to the benchmark, while values below 1 indicate that the model is performing better than the benchmark, and values above 1 indicate a worse performance. A limitation to consider when interpreting MASE is that it does not indicate whether a model is actually accurate or not, only how it performs relative to a specific baseline. In summary, MASE is a useful metric for assessing a forecasting model's performance by comparing it to a simple baseline forecast. It provides a standardized accuracy measure that is not influenced by the scale of the data, making it valuable for cross-model and cross-dataset comparisons.

4.3 Model Selection

Model selection consists of assessing the trade-off between the goodness of fit and the complexity of a forecasting model within a training dataset. This evaluation is done by using information loss criteria that penalize models with a larger number of parameters. The primary goal is to avoid overfitting, a situation where a model captures excessive noise in the training data rather than the underlying patterns. Goodness of fit, in general, measures how well a statistical or predictive model aligns with the observed data. In simpler terms, it assesses how closely the model's predictions match the actual observations. A strong goodness of fit suggests that the model effectively captures the underlying patterns and relationships in the data. In the context of forecasting models, this aspect is crucial because it helps measure the accuracy of the model's predictions. If a forecasting model exhibits a good fit, it means that its predictions closely align with the historical data, indicating its potential to offer reliable forecasts in the future. Conversely, a poor fit suggests that the model is unable to adequately capture the data's patterns and may not perform well when making predictions. The information loss criteria commonly used in the evaluation process are:

- *Akaike Information Criterion* (AIC) [8] is used to assess the goodness of fit and complexity trade-off in a model. It quantifies how well the model fits the data while considering its complexity and penalizes models with a larger number of parameters. Lower AIC values indicate a better trade-off between goodness of fit and model complexity. The AIC formula is given by:

$$AIC = n * \ln\left(\frac{sse}{n}\right) + 2 * k$$
$$k = p + q + P + Q + c + 1$$

where *sse* is the sum of squared errors, *k* is the number of model parameters, *p* is the autoregressive order, q is the moving average order, *P* is the seasonal autoregressive order, *Q* is the seasonal moving average order, *c* is a binary term equal to 1 if the corresponding model has a constant coefficient for the trend, and 1 is for the error term. In the Akaike Information Criterion (AIC), the primary assumption regarding the probability distribution of the forecast errors or residuals is that they follow a normal distribution. Specifically, AIC assumes that the residuals are normally distributed with a mean of zero and allows for varying levels of dispersion or heteroscedasticity. The assumption that the residuals are normally distributed allows AIC to accurately evaluate the model's goodness of fit and balance it against the complexity of the model (as represented by the number of parameters k). It is important to note that if this assumption is significantly violated, meaning that the residuals do not follow a normal distribution, AIC might not provide accurate model selection results. In such cases, alternative model selection criteria designed to handle non-normal and heteroscedastic forecast errors may be more appropriate.

- *Corrected Akaike Information Criterion* (AICc) [9] is used to balance the goodness of fit and model complexity when working with limited data samples. It is a modification of the Akaike Information Criterion (AIC) tailored for cases where data is scarce, and overfitting is a concern. A key feature of the AICc is its consideration of sample size relative to the number of model parameters. AIC may tend to favor more complex models with more parameters when the sample size is small. This preference for complexity can be problematic, potentially leading to overfitting, where a model fits the noise in the data rather than the underlying patterns. The AICc addresses this bias by introducing a penalty term based on the sample size. In essence, it penalizes models with a larger number of parameters more heavily when dealing with smaller samples. This correction helps establish a better equilibrium between model complexity and goodness of fit. In summary, the AICc is particularly useful when comparing models with varying degrees of complexity and working with relatively small samples. It offers a more appropriate assessment of the trade-off between goodness of fit and complexity, thus preventing overly complex models from being favored due to smaller sample sizes. The AICc penalty term is proportional to the square of the number of parameters, serving as a safeguard against overfitting in situations with limited data. The formula for AICc is expressed by:

$$AIC_c = AIC + \frac{2 * k * (k + 1)}{n - k - 1},$$

where *n* is the number of observations and k is the number of model parameters.

- Schwarz *Bayesian Information Criterion* (BIC) [10] is a method used to assess the trade-off between the goodness of fit and model complexity. Like other information loss criteria, it penalizes models with an increasing number of parameters, but BIC tends to be stricter in this regard compared to AIC. BIC is expressed as:

$$BIC = n * \ln\left(\frac{sse}{n}\right) + k * \ln(n).$$

When utilizing BIC, there is a critical assumption made concerning the distribution of forecasting errors or residuals. Specifically, BIC assumes that these residuals follow a normal distribution with zero mean and constant variance. In simpler terms, it assumes that the errors are normally distributed and homoscedastic, meaning they have a consistent variance across all observations. This assumption is essential because it forms the basis for how BIC penalizes models. BIC penalizes models that incorporate an excessive number of parameters relative to the amount of available data. Models with more parameters are more flexible and can potentially fit the data more closely, but they also come with a higher risk of overfitting. By imposing penalties on models with an excess of parameters, BIC aims to model complexity and goodness of fit. However, if the assumption of normality and constant variance for the residuals is significantly violated, BIC may not offer accurate model selection outcomes. In such instances, it may be more appropriate to consider alternative model selection criteria designed to handle non-normal and heteroscedastic forecast errors.

The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are the model selection criteria used in this work, but they differ in several key aspects. Hence, it is beneficial to compare the two criteria:

- *Philosophy:* AIC is based on information theory and attempts to balance model fit and model complexity. It favors models that fit the data well but penalizes models with a large number of parameters. BIC is derived from Bayesian statistics and is more conservative. It not only penalizes models for complexity but also favors simpler models with fewer parameters.
- *Penalty for model complexity:* AIC applies a less conservative penalty for model complexity compared to BIC. It allows for more flexibility in terms of model complexity, which can be an advantage when dealing with complex data or when a more flexible model is needed. In contrast, BIC imposes a more substantial penalty for model complexity. This results in a

preference for simpler models, making it a more conservative choice when selecting models.

- *Sample size:* AIC tends to perform better when the sample size is relatively large compared to the number of parameters, as it is less likely to favor overly complex models. BIC is more suitable when dealing with smaller sample sizes, as its stronger penalty for complexity helps protect against overfitting.
- *Normality assumption:* AIC assumes that the forecast errors (or residuals) follow a normal distribution but allows for heteroscedasticity (varying variance). BIC also assumes normality for the residuals but with the additional assumption of constant variance (homoscedasticity) across all observations.
- *Model selection criteria:* AIC often leads to the selection of more complex models when there is a trade-off between model fit and complexity. BIC tends to favor simpler models, even if they have slightly lower goodness of fit, due to its more stringent penalty for complexity.

In summary, AIC and BIC differ in their approach to model selection, with AIC being more flexible and favoring model fit, while BIC is more conservative and prefers simpler models. The choice between them depends on the specific goals of the analysis, the sample size, and the nature of the data. AIC assumes normality in the distribution of errors but allows for heteroscedasticity, meaning the variance of the residuals can vary across observations. This flexibility in allowing for varying levels of dispersion in the residuals makes the AIC a more robust choice when dealing with situations where the assumption of constant variance is not satisfied, and the residuals exhibit different levels of spread or dispersion. When choosing a forecasting model using criteria such as AIC or BIC, it is a common practice to compare the AIC or BIC values of various models. The model that exhibits the lowest AIC or BIC is generally regarded as the most appropriate choice.

5. Simple Forecasting Methods

This Section analyzes straightforward forecasting techniques, including the arithmetic mean, random walk, seasonal random walk, and random walk with drift, providing a foundational understanding of their principles, applications, and limitations. Simple methods serve as benchmarks for more sophisticated approaches and provide a starting point for assessing the consistency of predictions and establishing a basis for comparison. The four simple forecasting methods explored in this Section lay the groundwork for understanding the essentials of forecasting.

5.1 Multistep Forecasting vs One-step Forecasting without Re-estimation

Multistep forecasting consists of forecasts done at the beginning of the testing range for the full testing range without using testing range data. In contrast, one-step forecasting without re-estimation consists of forecasts done using the model's parameters estimated in the training range and the testing range data without re-estimating the parameters obtained in the training range.

One-step forecasting is referred to as "without re-estimation" because it involves making forecasts for just the next single time step without re-calculating or re-estimating the model's parameters as new observations become available. In other words, the process of forecasting is repeated step by step using the same model's parameters for each individual time step. In contrast, in multistep forecasting we make predictions for multiple future time steps (over the entire testing range). Both one-step and multistep forecasting approaches have their own advantages and limitations. Multistep forecasting is simpler and computationally less intensive, but it might not capture evolving patterns in the data; hence, it can provide less accurate forecasts over longer horizons. Moreover, multistep forecasting consists of out-of-sample forecasting, while one-step forecasting without re-estimation consists of in-sample forecasting but using the new testing range data.

5.2 Arithmetic Mean Method

The Arithmetic Mean method is one of the simplest and most straightforward techniques used for forecasting time series data. It computes the average or mean of historical observations (in the training set) and uses this value as the forecast for future time periods (in the testing set). The formula for the Arithmetic Mean method is quite simple, and the step-by-step process to apply for this model is:

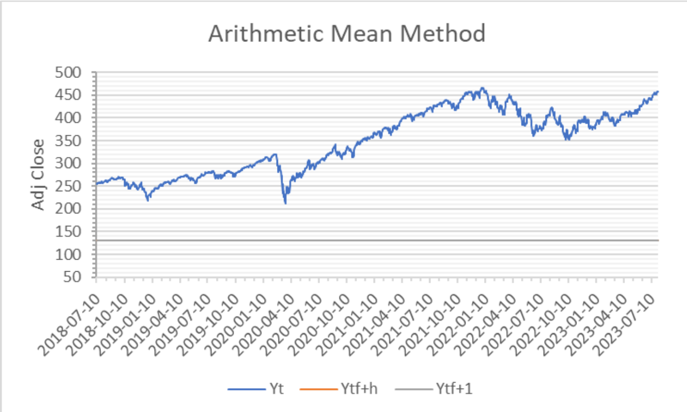
1. Collect the time series data representing past observations (in our case the historical data in the training set);
2. Calculate the mean: Add up all the historical values and divide the sum by the number of data points of the previous period historical data (training range);

$$\hat{y}_t = \mu = \frac{1}{n-1}\sum_{t=2}^{n} y_t$$

3. Forecast future values: Use the calculated mean as the forecast for all future time periods $\hat{y}_t$.

The arithmetic mean method is useful when the data is relatively stable over time and does not exhibit significant trends, seasonality, or other complex patterns. It provides a baseline or naive forecast that can serve as a starting point for more sophisticated forecasting techniques. However, it is essential to be cautious while using the mean method for forecasting, especially if the data contains outliers or exhibits significant variations. In such cases, the mean method may not capture the underlying patterns accurately and may lead to inaccurate predictions. Overall, the mean method is a simple and fast approach for forecasting when dealing with relatively stable and straightforward time series data. The model is trained on the training range and then exercised for forecasting in the testing range, using multistep forecasting with a multistep period *h* corresponding to the length of the testing range $(\hat{y}_{t+h})$, and one-step forecasting without re-estimation $(\hat{y}_{t+1})$. In this case the two methods yield the same results, as shown in Figure 6, where the $\hat{y}_{t+h}$ and $\hat{y}_{t+1}$ plots overlap.

Figure 6. Arithmetic mean in the testing range



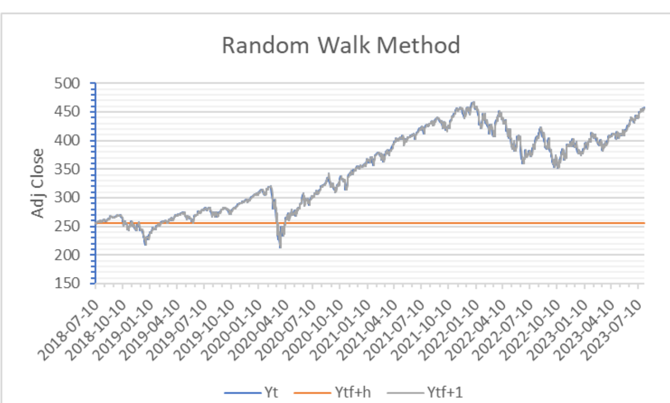
5.3 Random Walk Method

The Random Walk method is a simple and basic time series forecasting technique that assumes that future values will be equal to the last observed value. In other words, this approach is based on the idea that future variations are unpredictable, that the series will follow a "random walk" [11] and will continue its recent direction or behavior, making the last known value the best estimate for upcoming periods. The formula for the random walk forecast is given by:

$$\hat{y}_t = y_{t-1},$$

where $\hat{y}_t$ is the forecast for the next period, and y_{t-1} is the last observed value. The Random Walk method is often used for short-term forecasting when there is little information about underlying trends or patterns in the data. It is especially applicable when the data is relatively stable, and there are no significant trends or seasonality. However, the Random Walk method is not suitable for long-term forecasting or when the data has clear patterns or seasonality. The Random Walk method forecasting results are shown in Figure 7. The multistep forecasting $\hat{y}_{t+h}$ for the Random Walk considers the last value of the training range and repeats it for the full testing range.

Figure 7. Random walk in the testing range



5.4 Seasonal Random Walk Method

The Random Walk method can be improved by introducing more sophisticated forecasting techniques that take into account trends, seasonality, and other factors affecting the time series data. The Seasonal Random Walk is an extension of the basic Random Walk method that incorporates seasonality into the forecast. It is used when the time series exhibits clear seasonal patterns or cyclic behavior. In the Seasonal Random Walk method, the forecast for the next time period is calculated as the value from the corresponding seasonal period in the previous season. The formula for the Seasonal Random Walk forecast is:

$$\hat{y}_t = y_{t-m},$$

where on a daily time frame, *m = 21* days in a business calendar represents a monthly seasonality. Monthly seasonality refers to the regular and predictable patterns or fluctuations that occur monthly. In many real-world scenarios, certain events, behaviors, or factors tend to follow a monthly pattern, leading to recurring patterns in the data over each month. For example, in retail, there might be a higher demand for certain products around the end of the month, when people receive their paychecks. Like the basic Random Walk method, the Seasonal Random Walk is relatively simple and can be useful for short-term forecasting when the data shows stable seasonal patterns. However, it may not be appropriate for long-term forecasting or when the seasonality in the data is subject to significant changes or irregular patterns. The forecasts of the seasonal random walk in the testing range are depicted in Figure 8, while Figure 9 shows a zoom-in to better assess the results obtained by the multistep forecasting and the one-step forecasting without re-estimation methods.

Figure 8. Seasonal random walk in the testing range

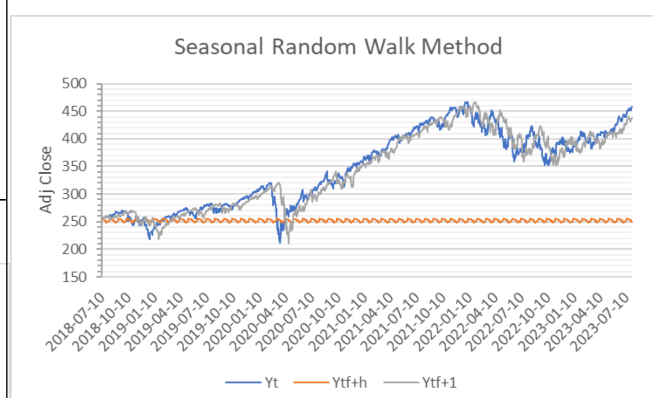


Figure 9. Seasonal random walk in the testing range: Zoom-in

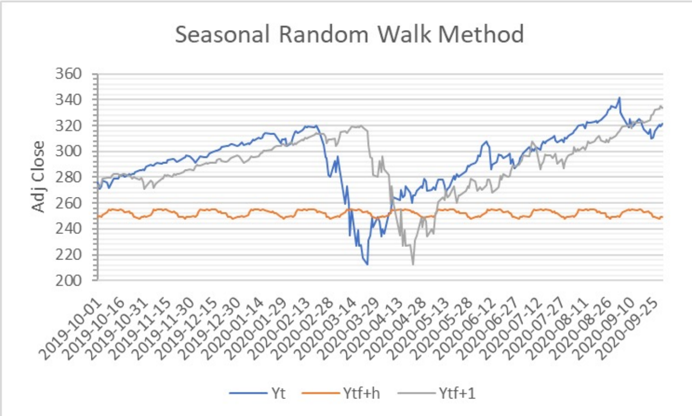
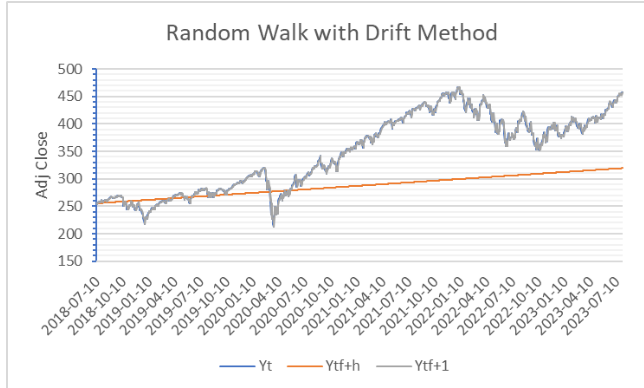


Figure 10. Random walk with drift in the testing range



5.5 Random Walk with Drift Method

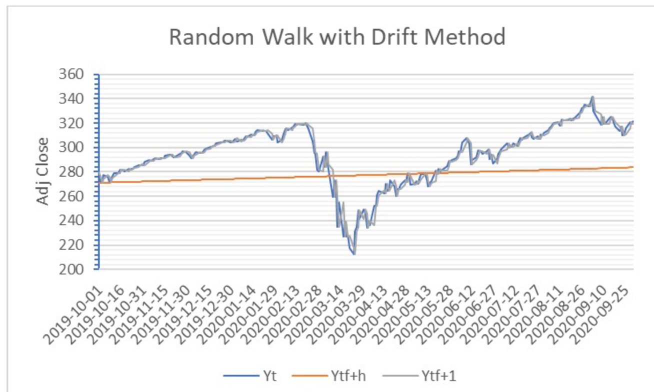
The Random Walk with Drift method consists of forecasts equal to the previous period data plus the arithmetic mean of previous periods historical data differences. The Random Walk with Drift is an extension of the basic Random Walk forecasting method, which includes an additional constant term or drift component to account for a trend in the data. In the Random Walk with Drift method, the forecast for the next period is calculated as the last observed value plus the drift term. The formula for the Random Walk with Drift method is given by:

$$\hat{y}_t = y_{t-1} + \delta$$

$$\delta = \frac{1}{n-2}\sum_{t=3}^{n}(y_{t-1} - y_{t-2})$$

where δ is the drift term representing the trend in the data, $\hat{y}_t$ is the forecast for the next period and y_{t-1} is the last observed value. The drift term δ indicates the average change or slope in the time series data over time and is computed in the training range. If the drift term is positive, it suggests a gradual upward trend in the data. Conversely, if the drift term is negative, it indicates a downward trend. If the drift term is zero, the Random Walk with Drift reduces to the basic Random Walk. The Random Walk with Drift is useful when the time series data exhibits a clear trend, and it provides a simple way to account for this trend in forecasting. However, it is important to note that Random Walk with Drift may not capture more complex trend patterns or sudden changes in the data. The results of the multistep and one-step forecasting without re-estimation are reported in Figure 10, while Figure 11 shows the corresponding zoom-in.

Figure 11. Random walk with drift in the testing range: Zoom-in



In one-step forecasting without re-estimation, we are not re-estimating the corresponding drift and we include a constant drift in the model. The challenge with multistep forecasting in Random Walk with Drift is that the uncertainty and randomness accumulate as we project further into the future. This means that the confidence in our predictions tends to decrease moving farther away from the present time. In practice, multistep forecasting in the context of Random Walk with Drift can be useful for certain types of time series data, where the underlying trend is expected to continue over a certain period.

5.6 Forecasting Accuracy

The forecasting accuracy metrics described in Section 4 have been used to evaluate the performance of the simple methods presented in this Section. In particular, we considered the metrics RSME (scale-dependent) and MAPE (scale-independent). The numerical results are reported in Table 1.

Table 1. Simple methods forecasting accuracy results

	Arithmetic Mean		Random Walk		Seasonal Random Walk		Random Walk with Drift	
	Ytf+h	Ytf+1	Ytf+h	Ytf+1	Ytf+h	Ytf+1	Ytf+h	Ytf+1
mae	216.5530	216.5530	93.3203	3.0025	96.0226	14.1297	63.3423	2.9985
rmse	227.3472	227.3472	114.7213	4.3385	117.2735	18.6680	80.1516	4.3369
mape	60.8159	60.8159	23.9925	0.8864	24.7544	4.2154	16.2194	0.8852
mase	56.7171	56.7171	24.4414	0.7864	25.1491	3.7007	16.5899	0.7853

Regarding multistep forecasting, Random Walk with Drift obtained the lowest RMSE and MAPE values, therefore the highest forecasting accuracy. For one-step forecasting without re-estimation both for RSME and MAPE the Random Walk with Drift achieved the lowest values, thus confirming the highest forecasting accuracy.

Footnotes

1 Certified SIAT Technical Analyst – SIAT (Società' Italiana Analisi Tecnica)

2 In this work, we use daily data on a business calendar, and we approximate the monthly seasonality to 21 days, therefore m = 21.

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Trend-Adaptation of Moving Averages (TAMA)

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Abstract

Largely unnoticed so far, Moving Averages (MAs) exhibit a trend bias: They underestimate (overestimate) the true value of the underlying asset during upward (downward) trends. This can not only result in misleading interpretations and forecasts, it also propagates to downstream indicators and ultimately the whole trading system. In this paper, we propose a robust method – TAMA – to correct the bias, i.e., to make any MA trend-adaptive. We exemplify this for common MAs and evaluate the effects qualitatively and quantitatively. Our findings indicate that trend adaptation greatly improves their performance in typical use cases. Additionally, we outline some new chart analysis tools that could be derived from TAMA: a Harmonic MA, a forecasting procedure, and a bands indicator.

1. Introduction

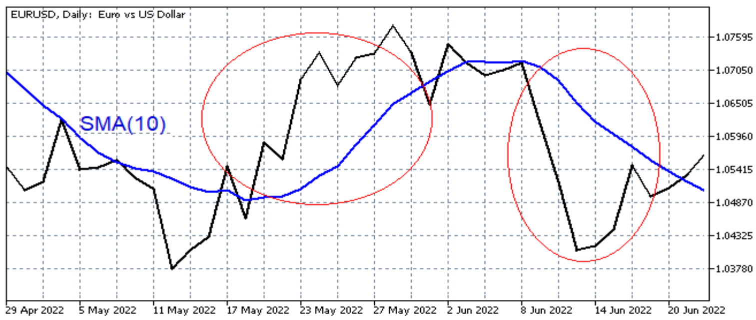
Moving Averages (MAs) are among the most fundamental tools of technical analysis. Their primary job is to filter out quasi-random noise from a price development – smoothing it thereby –, which is supposed to allow a better insight into the current "true value" of the underlying asset. Analysts then can interpret this value directly, forecast the continuation based on it, or use it as input for downstream indicators (e.g., the MACD or Bollinger Bands) and trading systems.

For all these applications, it is obviously of crucial importance that the MA's value actually represents the asset's true value without distortion, i.e., unbiased. If it does not, interpretations and forecasts could be misleading, and, even worse, downstream indicators and trading systems could produce wrong signals *without anyone noticing*, as the MA input is subsumed by them.

Fortunately, most commonly used MAs are unbiased. This is at least what many traders believe, and for good reasons indeed: When we look at the formula of the Simple MA (SMA), for instance, it is identical to the formula of the arithmetic mean, which is theoretically known to be not only unbiased but even the best unbiased linear estimator under some conditions (BLUE; e.g., Blom 1976).

In the practice of technical analysis, however, cases occur daily like the one exemplarily shown in Figure 1 (for the EUR/USD exchange rate in mid-2022): The employed MAs – regardless of their concrete specifics – seem to systematically underestimate price movements during upward trends and systematically overestimate them during downward trends (red circles) – and thus not to be unbiased at all!

Figure 1: Typical bias of MAs during trends.



We will investigate where this apparent contradiction comes from in a moment, but let us first stay with the figure and ask another question: Since it can clearly be seen that – and even how far – the MA is from the price, can it then not simply be shifted mathematically just as it can be mentally, formally correcting its distortion? This is in fact possible, but unfortunately only if the price development is viewed retrospectively (as we do it here), i.e., if one already knows when trends have occurred. The usual intention to use an MA is to calculate it during the ongoing price development ("online"), of course, and at those points in time, the data necessary for such a correction are obviously not yet available. This may also be a main reason why MAs, despite their great importance, still have not been trend-adapted.

However, this does not mean that the approach has to be abandoned altogether. Although the trend is not fully foreseeable at the time of MA calculation, methods exist to estimate it, even robustly despite the then very short trend window, and the information obtained thereby can be integrated into the MA. In the following, we will develop a rather simple method to achieve this (Section 2) and show then, in Section 3, how it can be used to make *any* MA trend-adaptive[1], i.e., to remove its bias during trends to a large extent. Our particular method also allows for some unique extensions, which are presented in Section 4. In Section 5, we evaluate by data whether and, if so, by how much MAs can be improved this way regarding their typical use cases. Section 6 finally concludes this work with some outlooks for future research.

2. The TAMA Method

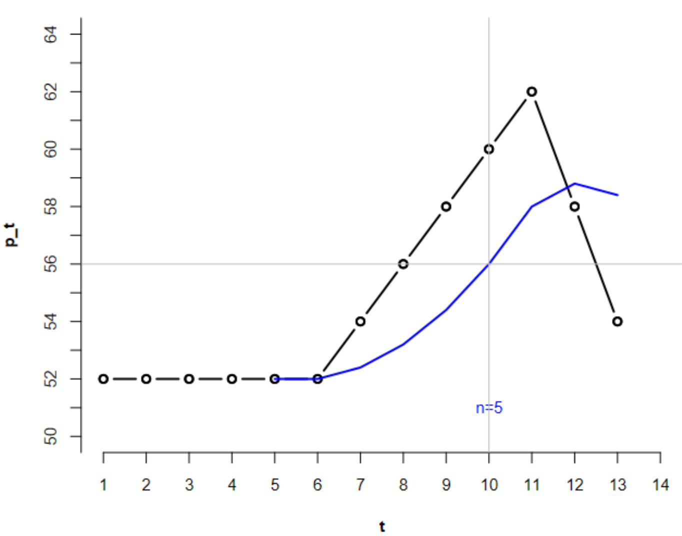
2.1 A Closer Look at the Problem

Let us now return to the aforementioned seeming contradiction: Why does a MA like the SMA, which has a formula that is theoretically unbiased, still exhibit a bias during trends?

The reason for this lies in the fact that the prices p_t are not realizations of the same – especially identically distributed – random variable, as it is assumed in the calculation of the arithmetic mean (i.e., they do not form a sample). Rather, each price p_t should be interpreted as the sole realization of its *own* random variable P_t, and it is by no means guaranteed that this variable must have the same distribution – or even the same location (or expectation) – as the previous one (P_{t-1}). On the contrary: It is precisely the *definition* of a trend that this is not the case.

Figure 2 illustrates this problem with an idealized price development smoothed by a 5-period SMA, examined at each point in time t at the end of a day, without knowledge of the future. First consider $t = 5$. The price has stayed at a value of 52 for five consecutive days here; thus, $SMA_5(5)=1/5 \cdot 5 \cdot 52=52$. This would also be the best possible forecast for $t = 6$; and indeed, that day ends again with a value of 52. Therefore, $SMA_5(6)=52$, and the previous forecast would now also be the best for $t = 7$. But things turn out differently: The price now rises to 54. This information is one that holds significance for analysts. As a counter example, consider $t = 10$: The price here has increased equidistantly for five consecutive days. Under the paradigm that all price values between $t = 6$ and $t = 10$ were drawn from the same distribution, the best estimate of their expected value – and thus the best smoothing for $t = 10$ as well as the best forecast for $t = 11$ – would indeed be that of the SMA, namely $SMA_5(10)=1/5 \cdot (52+54+56+58+60)=56$. Under the paradigm that a trend exists, i.e., $E(P_t)=E(P_{t-1})+m$ for a constant m (here $m = 2$), the corresponding values would, in contrast, lie exactly on the trendline, at 60 for $t = 10$ and at 62 for $t = 11$. The deviation of the SMA from this is therefore irrelevant – or rather *misleading* – information for analysts under the latter paradigm, since it merely results from the mathematical neglect of the trend.

Figure 2: Idealized price development with an SMA(5).



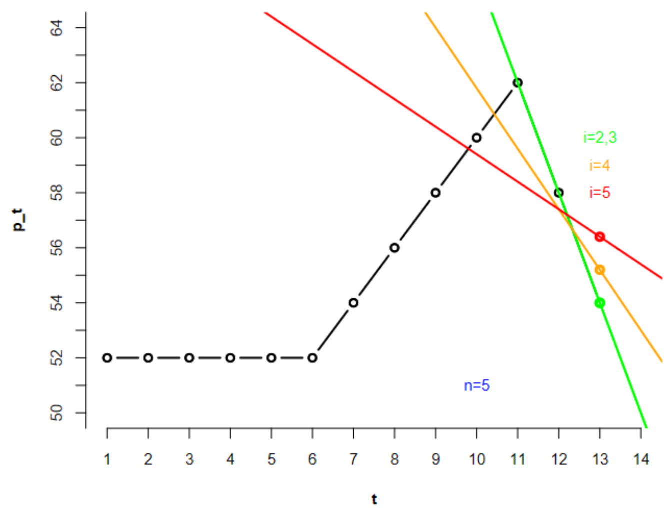
2.2 Idea and Approach

But how can one know which paradigm is the correct one in each case? Absolute certainty only comes in hindsight; while the price is evolving, estimations are necessary. Fortunately, the situation without a trend can easily be modelled as a special case of the situation with a trend, and then it can be evaluated based on the past price how likely this special case is.

The most intuitive approach that comes to mind may be to create a simple linear regression model of the price development with the time index as the only explanatory variable and to train it then with the data from the current MA-window (so for an n-period MA at time t, using the prices p_{t-n+1} to p_t). The estimated value $\hat{p}_t$ for p_t (even though this price is already known!) that results from the regression line obtained this way could then represent the value of the trend-adaptive MA at t.

In fact, this approach corresponds mathematically to the trend-adaptive version of the SMA (the TASMA), as we will see later.[2] However, it has some significant weaknesses (also when compared to other TAMA variants); in particular, it is not robust, e.g., regarding the choice of n. Figure 3 illustrates this problem and its solution based on the price development from Figure 2.

Figure 3: Various regression lines with trend on the price development from Figure 2.



Let us first consider only the red line. This is the regression line that would result from the process described above for $n = 5$. Its calculation has included the entire downtrend present at the current time $t = 13$, i.e., the points $t = 13$, $t = 12$, and $t = 11$, but also the points $t = 10$ and $t = 9$, which – though only clearly recognizable in this illustrative example – do not belong to it. If a different period length had been chosen instead, another line would have resulted, e.g. the green one for $n = 3$, which hits the trend much better. So the choice is not irrelevant, and the trend will not always have started just by chance at the edge of the period window. Introducing a parameter $i \leq n$ that lets the user specify a different start time would also not help much, as this parameter is not known, and certainly not the same for all windows.

The idea for "robustifying" the regression is therefore to perform it not only for *one* point in time of the window, but for *all* points in time $t - i + 1$ within it (cf. lines in Figure 3), i.e., multiple times. Then, a trend that starts only after the left edge of the window, as it is the case in the illustration, is still found. Additionally, while points that do not belong to it still have an influence on some estimates, only the "more leftward" ones are affected by this anymore (in the example for $i \in [4;5]$). The (overall) estimate $\hat{p}_t$ for p_t is then obtained as an average of the individual estimates $\hat{p}_{t_i}$ (cf. coloured dots).

2.3 Formalization

We will now formalize this idea, proceeding "backwards" from the last step to the first. This last step is the calculation of an average of the price estimates $\hat{p}_t$ at time t:

$$TAGMA_n(t) = \frac{1}{n} \cdot \sum_{i=1}^{n} w_i \cdot \widehat{p}_{t_i} + r(t). \qquad (1)$$

To take into account that there are multiple ways to calculate "an average", we have introduced here weights w_i and a residual constant $r(t)$ that may depend on t but not on the price estimates. This flexibility will play a crucial role later, and it will also become clear then why we have denoted the result as $TAGMA_n(t)$.

The i-th price estimate should be the result of its own linear regression, thus lie on the corresponding regression line. Denoting $\hat{\alpha}_i$ as its intercept and $\hat{\beta}_i$ as its slope, then $\hat{p}_{t_i}$ can be formalized as

$$\widehat{p}_{t_i} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} \cdot i, \qquad (2)$$

since what is sought is the i-th point on the line in each case. To illustrate, it is helpful to look at Figure 3 again, for example for i=3 (green line): This is estimated by the points p_{11}, p_{12}, and p_{13}, and if we number these from left to right, the estimation time $t = 13$ corresponds exactly to the i-th (and last) point.

(2) refers to simple linear regressions, and for such, general formulas for the straightforward calculation of $\hat{\alpha}_i$ and $\hat{\beta}_i$ are known.[3] Adapted to our case, the following relationships are derived (see Appendix):

$$\hat{\alpha}_{t,i} = \bar{p}_{t,i} - \hat{\beta}_{t,i} \cdot \frac{i+1}{2} \quad \text{and} \qquad (3a)$$

$$\hat{\beta}_{t,i} = \begin{cases} \frac{12}{i^3 - i} \cdot \sum_{j=1}^{i} \left(j - \frac{i+1}{2}\right) \cdot (p_{t-i+j} - \bar{p}_{t,i}), & \text{if } i > 1 \\ 0, & \text{else} \end{cases} \qquad (3b)$$

where $\overline{p}_{t,i}$ denotes the arithmetic mean of the prices from p_{t-i+1} to p_t.

3. From MA to TAMA

3.1 General Procedure

Now that we have formalized our idea, we could call the TAGMA a new indicator, choose any weights w_i and any residual $r(t)$ for it, and include it in our trading system to replace the classical MAs.

However, our actual goal was different: Instead of replacing the classical MAs by something new, we just wanted to trend-correct them. This means that what remains is to find a relationship between any MA – call it "Generic MA" (GMA) – and its trend-adaptive (TA) version, the TAGMA (hence the name).

To do so, we start with the formula that (almost)[4] every concrete MA is a special case of:

$$GMA_n(t) = \sum_{i=1}^{n} u_i \cdot p_{t-i+1} + s(t), \qquad (4)$$

with weights u_i (which can, of course, also be 0) and a price-constant residual $s(t)$, both factors to characterize the concrete MA. This almost looks like the definition of the TAGMA in (1) already, but there is an important difference: The GMA is based on different actual prices p_{t-i+1}, while the TAGMA is based on different estimates $\hat{p}_{t_i}$ of the *same* price p_t.[5]

To make both approaches comparable, an essential insight is required: If the TAGMA is the TA-version of the GMA, it must match the latter *for all arbitrary price values and points in time* when trend adaptation is "turned off". We will later introduce that capability as an extension to the TAMA method in more detail; for now, it should suffice to say that TA enters (2) through the dynamic slope coefficient $\hat{\beta}_{t,i}$ and thus can be deactivated by setting $\hat{\beta}_{t,i} = 0$ instead of its value from (3b). Using (2) and (3a) with this, we can demand the following equality independent of specific price values:

$$TAGMA_{n,TA=0}(t) = \frac{1}{n} \cdot \sum_{i=1}^{n} w_i \cdot \bar{p}_{t,i} + r(t) \overset{!}{=} \sum_{i=1}^{n} u_i \cdot p_{t-i+1} + s(t) = GMA_n(t). \qquad (5)$$

One can show (see Appendix) that this is satisfied if and only if the concretization parameters of the TAGMA are chosen as follows:

$$w_i = \begin{cases} n \cdot i \cdot (u_i - u_{i+1}), & \text{if } i < n \\ n^2 \cdot u_n, & \text{else (if } i = n) \end{cases} \quad \text{and} \qquad (6a)$$

$$r(t) = s(t). \qquad (6b)$$

Thus, a fairly simple relationship has been found that allows the calculation of the weights for the corresponding TAMA with deactivated trend adaptation from the knowledge of the MA's formula. With the "reactivation" of TA by re-setting $\hat{\beta}_{t,i}$ to its value from (3b), its construction is complete.

3.2 TA-versions of Common MAs

We can now apply our newly found relationship to any MA, and we will do so in the following for the three arguably most common MAs. Our approaches will be illustrative for other MAs as well.

Simple Moving Average (SMA)

The SMA is characterized by $u_i = \frac{1}{n}$ and $s(t) = 0$. Thus, we have from (6a):

$$w_i^{SMA} = \begin{cases} n \cdot i \cdot \left(\frac{1}{n} - \frac{1}{n}\right), & \text{if } i < n \\ n^2 \cdot \frac{1}{n}, & \text{else} \end{cases} = \begin{cases} 0, & \text{if } i < n \\ n, & \text{else (if } i = n) \end{cases} \qquad (7)$$

This means that all regressions except the "largest one" (the one taking into account all n points up to the beginning of the period window) are excluded from the calculation! Thus, the resulting TASMA is based only on this single regression, making it generally fragile and sensitive to the choice of n. This issue has been discussed in more detail in Section 2.1. As a consequence of it, the TASMA is usually more of theoretical interest and not recommended to be used in practice.

Weighted Moving Average (WMA)

The Weighted MA (WMA) is based on the idea of assigning the weight $u_i = \frac{n-i+1}{N}$ to the price p_{t-i+1}, which is $i - 1$ days away from the current price p_t, so that older influences linearly decrease in importance compared to newer ones. Here, $N = n + (n - 1) + \ldots + 1 = \frac{n^2+n}{2}$ is a normalization factor. According to (6a), the weights of the TAWMA are determined as follows:

$$w_i^{WMA} = \begin{cases} n \cdot i \cdot \left(\frac{n-i+1}{N} - \frac{n-(i+1)+1}{N}\right), & \text{if } i < n \\ n^2 \cdot \frac{1}{N}, & \text{else (if } i = n) \end{cases} = \frac{2 \cdot i}{n+1}. \qquad (8)$$

Similar to the SMA, the WMA represents an interesting special case in a sense, as the otherwise necessary distinction in (6a) is not needed due to the arithmetic progression of its weights.

Exponential Moving Average (EMA)

The Exponential MA (EMA) extends the idea of the WMA; it also weights prices less that are further back in time, but by an exponential progression:

$$\begin{aligned} EMA_{n,\alpha}(t) &= \alpha \cdot p_t + (1-\alpha) \cdot EMA_n(t-1) = \alpha \cdot \sum_{i=1}^{\infty} (1-\alpha)^{i-1} \cdot p_{t-i+1} \\ &= \sum_{i=1}^{n} \alpha \cdot (1-\alpha)^{i-1} \cdot p_{t-i+1} + \underbrace{\sum_{i=n+1}^{\infty} \alpha \cdot (1-\alpha)^{i-1} \cdot p_{t-i+1}}_{r(t)} \end{aligned} \qquad (9)$$

with a smoothing factor $0 < \alpha < 1$, which is typically but not necessarily chosen as $\alpha = \frac{2}{n+1}$. Consequently, the weights become progressively smaller, but they never reach the value of 0 and thus never disappear in theory.[6] At first glance, this might seem problematic, as only a weighted sum of precisely n prices within the current period window has been allowed so far.

However, if one decomposes the calculation formula as shown in (9), the issue becomes easily resolvable: All other prices for $i \geq n$, including their coefficients, do not enter the weights w_i but are instead represented by the residual term $r(t)$; this term must be constant with respect to the prices in the window, but not necessarily with regard to the other ones. Thus, the weights w_i can be determined as usual from (6a):

$$\begin{aligned} w_i^{EMA} &= \begin{cases} n \cdot i \cdot (\alpha \cdot (1-\alpha)^{i-1} - \alpha \cdot (1-\alpha)^i), & \text{if } i < n \\ n^2 \cdot \alpha \cdot (1-\alpha)^{i-1}, & \text{else (if } i = n) \end{cases} \\ &= n \cdot i \cdot \alpha \cdot (1-\alpha)^{i-1} \cdot \left(\begin{cases} \alpha, & \text{if } i < n \\ 1, & \text{else (if } i = n) \end{cases}\right). \end{aligned} \qquad (10)$$

3.3 The "Simplest" TAMA: The TAHMA

One might have expected that the simplest concretization of the TAGMA in (1), which can be constructed by choosing equal weights of w_i=1 for all i and a residual of $r(t)$=0, making the calculated average the arithmetic mean, were the TA-version of the SMA, since the latter also uses equal weights and no residual. However, by (7) we have found that this is not the case. Instead, it can be shown (cf. derivation of (6a) and (6b)) that the MA that corresponds to the "simplest" TAMA — the TAHMA — looks like follows:

$$\begin{aligned} HMA_n(t) &= \frac{1}{n} \cdot \left(\frac{1}{1} + \cdots + \frac{1}{n}\right) \cdot p_t + \frac{1}{n} \cdot \left(\frac{1}{2} + \cdots + \frac{1}{n}\right) \cdot p_{t-1} + \cdots + \frac{1}{n} \cdot \left(\frac{1}{n}\right) \cdot p_{t-n+1} \\ &= \frac{1}{n} \cdot \sum_{i=1}^{n} (H_n - H_{i-1}) \cdot p_{t-i+1}, \end{aligned} \qquad (11)$$

where $H_i = \sum_{j=1}^{i} \frac{1}{j}$

denotes the i-th so-called harmonic number, that is, the i-th partial sum of the harmonic series ($H_0 = 0$ is defined for notational reasons). We therefore call this MA the Harmonic MA (HMA).[7]

This relationship may appear surprising at first glance, but upon closer examination, it turns out to be very natural: The TAMA is by construction an average of regression estimates, those are also averages themselves, and the basis of the regressions are exactly $i = 1, 2, \ldots, n$ points. Now a *consecutive average of averages* corresponds precisely to the essence of the harmonic series.

This inherent connection to the method, its simplicity, and the weaknesses of the TASMA make the TAHMA an especially good candidate for practical use. In fact, we will see later that it also performs well; however, the difference between various TAMAs is generally not very pronounced.

4. Extensions

Now that we have found how the common TAMAs look like, we could proceed directly to their practical application. However, the particular method we have derived for trend adaptation allows for some special extensions that will proof useful there, so that we will introduce them beforehand.

4.1 Trend-Adaptation Switch TA

The first extension has already been mentioned and used to obtain (5): a "switch" that allows deactivating the trend adaptation if desired. This enables a direct evaluation of its effect.

The switch is formally a Boolean parameter, denoted here as *TA*, which is "true" (i.e., 1) by default and must be set to "false" (i.e., 0) to deactivate it. TA can be incorporated by modifying (3b) as follows:

$$\hat{\beta}_{t,i} = \begin{cases} 0, & \text{if } TA = 0 \\ \hat{\beta}_{t,i} \text{ from (3b)}, & \text{else (if } TA = 1) \end{cases} \quad (12)$$

The effect is immediately clear: Setting the slope of the line β $\hat{\beta}_{t,i}$ to 0 means nothing other than to *rule out* a trend – precisely as MAs implicitly do. This becomes evident in (2) in conjunction with (3a); since the terms associated with $\hat{\beta}_{t,i} = 0$ vanish, it simply holds that

$$\widehat{p_t}_i = \hat{\alpha}_{t,i} = \overline{p}_{t,i} = SMA_i(t).$$

4.2 Forecasting Period P

Many forecasting models for the future price development are based on MAs (see Nau 2014 for an introduction). Of course, TAMAs can also be used as inputs for such a model, and since they take into account not just averages but also their changes during trends, it would be unsurprising to obtain better predictions thereby alone. However, due to the particular calculation of TAMAs – after all, they are based on regression models – it is additionally possible to use them for forecasting *independently*.

A further extension is introduced for this: In (2), the price at time *t*, p_t, was estimated based on the corresponding point on the i-th regression line, which was found at index i. This was done solely for the purpose of smoothing (averaging), as p_t is already known at (or at the end of) *t*. The price at a later point in time $t + P$, on the other hand, is still unknown by then; of course, however, nothing prevents us from looking for it on the regression lines, too, just at index $i + P$ instead of *i*.

Formally, this requires introducing another parameter, here designated as *P* (for "prognosis" or "period"), which defaults to the value 0. (2) is then to be modified as follows:

$$\widehat{p_t}_i = \hat{\alpha}_{t-P,i} + \hat{\beta}_{t-P,i} \cdot (i + P). \quad (13)$$

(13) means that the i-th estimate $\widehat{p_t}_i$ for p_t is calculated based on the data available at time $t - P$, and then extrapolated *P* units into the future from there. Accordingly, a TAMA with this extension provides values not only up to *t* but up to $t + P$, as data are available exactly up to $t = (t + P) - P$.

P has been modelled here as any integer for maximum flexibility.[8] In practice, however, it is generally not advisable to attempt extrapolating the price by more than one unit of time; additionally, the estimation error naturally increases with the distance from the data available at *t*. *P* will therefore usually either have its default value of 0, for which (13) and (2) coincide, or be 1, so it effectively acts as a "forecasting switch".

4.3 Generic Aggregation Function AF

In (1), the *n* estimates $\widehat{p_t}_i$ for the price p_t at time *t* were aggregated to an overall estimate through averaging. Though this is the most intuitive method, it is not the only possible one. The right side of (1) can thus be replaced by a more generic aggregation function AF:

$$TAGMA_n(t) = AF\left(\widehat{p_t}_1, \ldots, \widehat{p_t}_n\right). \quad (14)$$

By default, *AF* should still correspond to a (linear) weighted average – in which case (14) is (1) –, but there are applications for which other aggregation functions are even more useful.

A prominent example for such an application are band indicators. Again, TAMAs could simply be used as a replacement for their conventional counterparts here and would likely perform better than these, since the generated bands are then laid around a mean value that more closely reflects the truth, and the interpretation does not need to depend anymore on whether there is a trend or not.

The TAMA method also entails a specific band indicator, however, when appropriate aggregation functions are used. For instance, a price development could be described and analysed using the 20%-quantile band, the 80%-quantile band, and possibly the median (i.e., the 50%-quantile band) of the estimated values $\widehat{p_t}_i$. This can even be used to build a trading system out of TAMA. We will demonstrate this idea later on.

5. Practical Evaluation

Having specified the TAMA method and its extensions completely, it is time to return to Figure 1, which has demonstrated the trend-problem of conventional MAs. Continuing the same example, we will now examine qualitatively whether the problem can be solved by TAMA and how this affects the typical use cases of MAs mentioned in the introduction: smoothing, forecasting, and downstream usage. We will also perform a small quantitative study to investigate their performance in the latter two areas.

5.1 Smoothing

Figure 4 reiterates Figure 1, but this time with a TAHMA added to it that has the same period duration (of 10) as the SMA we have looked at earlier, once with and once without trend adaptation.

Figure 4: Figure 1 extended by a TAHMA(10) with and without trend adaptation (TA).

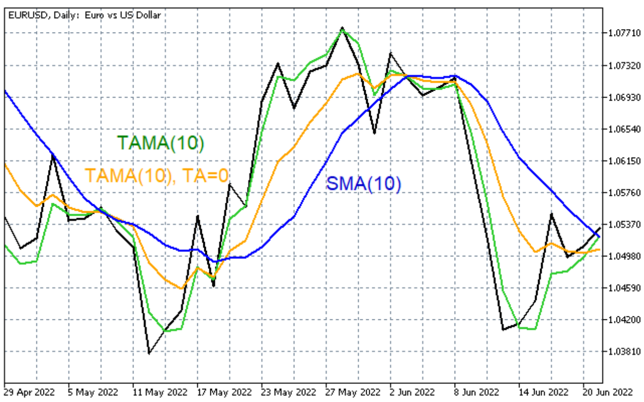
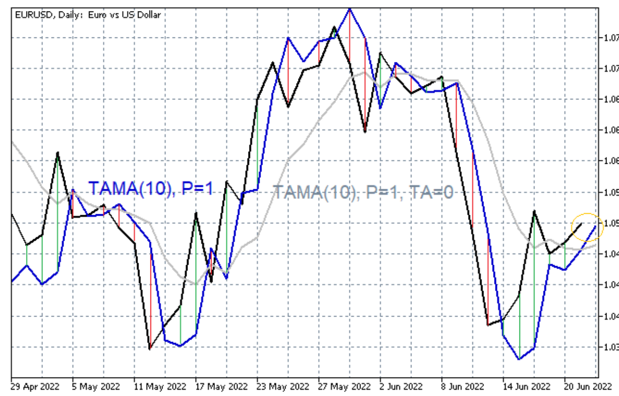


Figure 5: Exchange rate forecast using a TAHMA(10) with *P* = 1, with deviations from the actual price.



Let us first focus on the version without trend adaptation (orange line), which is equivalent to a HMA(10) from (11). While it is at the same "level" as the SMA, it already provides a smoother picture of the exchange rate: Not only is it practically closer to it at every point in time, it is also significantly less delayed. This results from the HMA, like an EMA, putting more emphasis on more recent prices. However, it can clearly be seen that the trend-problem (cf. red circles in Figure 1) is not solved yet.

That is only achieved when trend-adaptation is switched on, resulting in the actual TAHMA(10) (green line): Both during the upward and downward trends, it not only stays very close to the exchange rate, as it should, but also is no longer systematically below or above it — it is indeed unbiased even during trends. Of course, this also means that with the same period, it smooths slightly less than conventional MAs; it is therefore a plausible recommendation to use somewhat longer period durations for TAMAs in general.

We would like to demonstrate the superiority of TAMAs for smoothing also quantitatively. However, that were challenging given that entire studies can be dedicated to the question alone how "smoothness" should be captured mathematically and weighed against the accuracy of price representation (e.g., Raudys and Pabarskaite 2016). However, it obviously is always preferable when the latter, given a certain level of the former, does not depend on whether the price "by chance" is in a trend or not, and since TAMAs do not exhibit this weakness anymore, they should dominate MAs in any quantitative investigation on smoothing.

5.2 Forecasting

Figure 5 again shows a TAHMA(10) for the USD exchange rate example (blue line, cf. green line in Figure 4), but this time with $P = 1$ instead of $P = 0$ — i.e., the value at t now only relies on data up to t-1. Consequently, it can now be plotted up to $t + 1$, forecasting the exchange rate for the next day (circle).

How accurate is this forecast over the whole window (blue line)? Examining it on its own at first, it can visually be deemed appropriate: It is usually not too far from the actual value (which is not known until the following day, of course); on some days, it is nearly exact (e.g., 09/05), on others (especially those with significant changes), the deviation is larger (e.g., 12/05). Over- and underestimations (red and green lines, resp.) generally balance each other out, although the former naturally occur more frequently during downward trends, while the latter occur more frequently during upward trends due to the MA basis.[9]

However, we are more interested here in the added value of trend adaptation. To evaluate this, let us first consider what it would mean to forecast a price using conventional MAs, i.e., without accounting for trends: The best possible prediction would then be the trivial one, i.e., assuming the price at $t + 1$ to have the value of the MA at t — in other words, simply shifting the MA one time unit to the right! This is illustrated by the grey line, for which trend adaptation was deactivated using the TA=0 switch: It corresponds exactly to the orange line from Figure 4, just shifted. The value added by the TAMA method can thus be directly determined by comparing the blue to the grey line: The former generally lies much closer to the actual value, especially during trends, corresponding to a significantly better forecast. This is not all that surprising, as dedicated approaches often also rely on regressions.

To quantify the extent of this improvement in general, we conducted a similar analysis as shown here for the 40 DAX members over a 1-year period (01/07/2021-30/06/2022) as example. Forecasting accuracy was measured using the Root Mean Square Error (RMSE), which (in principle) looks at the average size of an estimation residual (cf. red and green lines in Figure 5), independent of its direction. The predictions were based on an EMA with a period of 20 days vs. a TAEMA with the same period. Table 1 shows the results (columns 2-4). These are basically as expected: The estimation error was lower *for each* DAX member when trend adaptation was activated, as this makes additional information — specifically, information about trends — usable. However, the magnitude of this effect may be surprising: The RMSE for the TAEMA was on average lower by nearly 1/3 (31.97%) than for the EMA!

Despite these appealing characteristics, TAMAs likely should not be used as a sole forecasting model. While they can accurately capture averages and their changes, they lack a component that represents the variance around these values. This gap can be bridged, however; either through suitable combinations with "spread indicators" like the Stochastic Oscillator, or by forming and using bands, i.e., interval rather than point estimators. The latter approach is a special case of what will be discussed next.

5.3 Downstream Usage

Finally, we will evaluate whether trend adaptation improves not only MAs themselves but also their downstream usage, i.e., other indicators or whole trading systems that are based on them. As a well-known example for such a downstream indicator, we consider Bollinger Bands; these can also be regarded an example for the interval estimators mentioned above. They are constructed by placing a symmetric channel of size $2 \cdot 2 \cdot \sigma$ around a 20-period SMA in the standard setting, where σ denotes the standard deviation of prices in the current window (for details, see Bollinger 2001). Many investors believe that the price at the next time unit will then lie within this channel with a probability of about 95%. This is, of course, not true in general because none of the assumptions behind this rationale is actually given (incidentally, this is related to the problem discussed in Section 2.1). Nevertheless, there *is* a probability that the expected will happen; it just does not necessarily amount to 95%. Its actual value can be well estimated through backtesting; in our study, it averages around 82% (column 5 of Table 1). But this is only the case for the conventional SMA; if its trend-adaptive version, the TASMA, is used instead, the probability rises to over 90% (column 6), and with a TAEMA, it would still be higher — all for the *same channel size*. This again shows how trend adaptation can improve existing indicators.

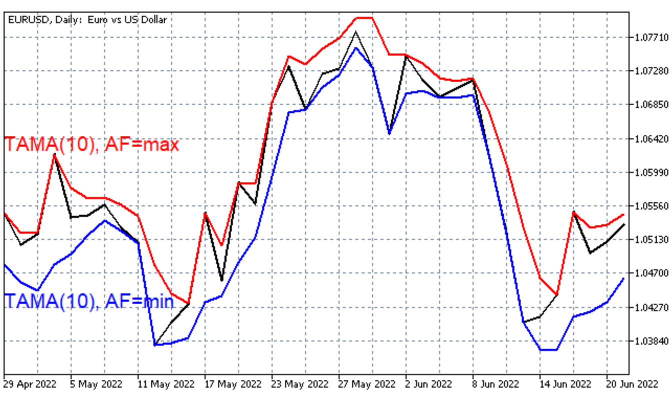
Table 1: Comparison of forecasts and bands with and without trend adaptation.

Asset 1/7/21-30/6/22	rmse_ta0	rmse_ta1	-%	boll_ta0	boll_ta1	boll_sig	mima	mima_sig
adidas	130.12	88.78	31.77%	81.36%	93.22%	2	76.17%	0.77
Airbus	58.39	44.30	24.14%	84.75%	87.71%	2	73.19%	0.92
Allianz	90.35	61.39	32.05%	81.78%	91.95%	2	75.74%	0.78
BASF	32.71	20.30	37.94%	81.36%	89.41%	2	77.45%	0.82
Bayer	27.75	16.34	41.11%	80.08%	91.95%	2	71.06%	0.72
Beiersdorf	34.29	26.03	24.10%	86.86%	86.44%	2	74.89%	0.93
BMW	45.34	31.16	31.27%	84.75%	91.95%	2	74.89%	0.83
Brenntag	30.42	22.14	27.23%	84.32%	89.41%	2	73.62%	0.90
Continental	65.30	42.88	34.33%	78.81%	89.83%	2	78.30%	0.79
Covestro	29.49	19.75	33.02%	78.81%	89.83%	2	75.32%	0.83
Daimler Truck	16.69	10.15	39.15%	80.00%	88.33%	2	79.83%	0.77
Deutsche Bank	9.66	6.12	36.64%	84.32%	87.71%	2	75.74%	0.80
Deutsche Börse	55.99	37.12	33.71%	80.08%	92.37%	2	75.32%	0.79
Deutsche Post	25.02	16.61	33.63%	80.93%	88.98%	2	74.89%	0.79
Deutsche Telekom	6.47	4.47	31.00%	82.63%	91.10%	2	75.32%	0.79
E.ON	4.40	2.95	32.80%	80.08%	92.80%	2	74.89%	0.81
Fresenius	19.15	11.28	41.09%	79.24%	94.07%	2	75.74%	0.69
Fresenius Medical Care	25.81	17.44	32.45%	82.20%	91.10%	2	74.89%	0.80
Hannover Rück	65.95	49.66	24.70%	80.51%	90.68%	2	72.34%	0.88
	31.61	20.92	33.83%	83.90%	91.95%	2	79.15%	0.77
HelloFresh	64.32	41.13	36.05%	79.24%	90.68%	2	76.17%	0.77
Henkel vz.	31.30	21.77	30.43%	79.66%	87.71%	2	75.74%	0.80
Infineon	21.25	13.82	34.99%	80.93%	90.25%	2	75.74%	0.77
Linde	109.46	74.28	32.14%	81.36%	90.68%	2	72.34%	0.79
Mercedes-Benz	51.03	34.84	31.72%	87.29%	87.71%	2	77.87%	0.79
Merck	102.64	63.70	37.94%	77.97%	90.68%	2	74.04%	0.73
MTU Aero Engines	104.40	76.85	26.38%	84.32%	88.98%	2	76.17%	0.83
Münchener Rück	107.14	74.11	30.83%	80.93%	94.07%	2	73.19%	0.79

Asset (1.7.21-30.6.22)	rmse_ta0	rmse_ta1	-%	boll_ta0	boll_ta1	boll_sig	mima	mima_sig
Porsche	55.81	42.22	24.36%	87.29%	88.98%	2	75.74%	0.85
PUMA	53.21	34.56	35.04%	80.51%	94.07%	2	77.02%	0.78
QIAGEN	18.29	13.62	25.56%	81.78%	89.41%	2	74.47%	0.88
RWE	15.68	12.48	20.42%	79.66%	91.10%	2	74.47%	0.90
SAP	43.96	29.07	33.87%	81.78%	92.37%	2	74.04%	0.76
Sartorius vz.	477.57	309.75	35.14%	82.63%	92.80%	2	76.17%	0.72
Siemens	72.59	51.51	29.04%	81.78%	87.71%	2	74.47%	0.85
Siemens Healthineers	29.67	21.00	29.21%	82.20%	89.83%	2	76.60%	0.86
Symrise	50.83	33.44	34.20%	80.93%	90.68%	2	75.32%	0.77
Volkswagen	100.70	74.26	26.26%	85.17%	88.14%	2	74.89%	0.89
Vonovia	21.35	14.77	30.81%	86.02%	93.64%	2	77.87%	0.83
Zalando	52.13	32.14	38.35%	80.08%	92.37%	2	74.89%	0.75
Average	**59.71**	**40.48**	**31.97%**	**81.96%**	**90.57%**	**2**	**75.40%**	**0.81**

In addition, as already has been mentioned in Section 4.3, the TAMA method also entails its own band indicator, and that will be the object of our last analysis. For this purpose, let us once again look at the example of the EUR/USD exchange rate with a TAHMA(10), but this time with the aggregations functions $AF = \min_i \hat{p}_{t_i}$ and $AF = \max_i \hat{p}_{t_i}$, respectively (Figure 6). Among all quantile-based functions, these are of particular interest because they create the extreme bands, which envelop the price and do never intersect. This may not sound too exciting at first, but it inspires two new evaluation possibilities:

Figure 6: min-max-Bands (AF) of TAHMA(10) around the exchange rate.

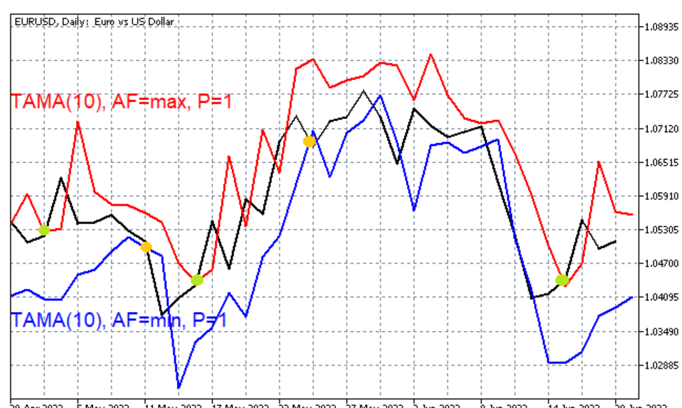


The first is the observation that the price is almost always closer to one band than to the other, often — but not always (e.g., 09/05, 30/05) — hitting the former. It can therefore be assumed that its distance to the bands represents information that can be used to determine the magnitude of the current trend.

The second idea may be even more interesting: If the minimum and maximum of the estimates for the price completely enclose it when p_t is known, what is the meaning of crossing this envelope when p_t is instead forecasted? After all, such a crossing means that the price then falls below or exceeds the smallest or largest possible extension of its current course; this should be a strong signal that something will change!

Figure 7 shows, to verify this, the content of Figure 6 but on a forecast basis, i.e., with $P = 1$. Indeed, there are several places where the envelope formed by the min-max-bands is crossed. Most of these crossings are sequential in the sense that the same band is pierced repeatedly one after another. This could be interpreted as a changing or (more likely) not yet stabilized (estimated) slope. However, more significant is the view of the respective *first* crossing points of a band after a breach point of the other (shown in green and orange in the figure). If these were interpreted as buy or sell signals in the example of the figure, one would have traded well, except for the very first case where an apparent uptrend did not materialize: The large uptrend in mid-May is recognized very promptly and exited exactly when a plateau sets in; another buy signal then occurs only in mid-June after the large downtrend is over.

Figure 7: Figure 6 on forecasting basis ($P = 1$), with respective first crossing points.



For a quantitative evaluation, the TAMA Bands were studied the same way as the Bollinger Bands. Their hit rate seems lower at first glance (column 8 of Table 1) – on average, 75% prices lie within their channel –, but this channel also is significantly narrower: It requires only about 0.8 standard deviations (column 9) instead of 2 (column 7). Therefore, the TAMA bands could be a good alternative for some applications.

6. Conclusion

In this paper, we have developed a regression-based method to correct the bias MAs exhibit during trends. The method includes a "switch" extension by which trend adaptation can always simply be turned on or off, enabling traders to evaluate its effects easily.

In our example study of 40 DAX members, we have found that turning it on greatly improves an MA's performance in smoothing, forecasting, and downstream usage: Forecasting errors were reduced by roughly 1/3 and Bollinger Bands became more consistent by roughly 10%. Future research can continue to evaluate such effects, e.g. for other MA-based indicators such as the MACD.

The particular variants of TAMAs generally do not differ much regarding performance from our experience, at least no more than the underlying MAs. An exception to this, however, is the TASMA, since its calculation effectively uses only a single regression, which is against the basic idea of TAMA of averaging multiple estimations for robustness. In contrast, the TAHMA we have introduced aligns most naturally with this idea, and thus it is the variant we recommend in the trend adaptation context.

Finally, we have outlined some ideas on what else could be derived from the TAMA method, namely a forecasting procedure and a bands indicator. Both tools also showed promising results in our practical evaluation and are therefore worthy of further exploration in future research.

Implementation for MetaTrader 5

The TAMA method has been implemented for the popular trading program MetaTrader 5 (for the MAs SMA, WMA, EMA, and HMA and the aggregation functions arithmetic mean, min, max, and quantile). It can be downloaded from the MQL5 marketplace (https://www.mql5.com/en/market).

Appendix

The appendix contains the mathematical derivations of (3a) and (3b) for one thing and of (6a) and (6b) for another thing. It has been omitted here for brevity but is available from the author upon request.

Footnotes

[1]"Adaptive" refers to the MAs, as will become clear later, dynamically adapting to trends. This has nothing to do with other "Adaptive MA" indicators, such as the one by Kaufman (1995, pp. 129-153).

[2]The TASMA described here (without the forthcoming extensions) is essentially identical to the widely discussed Linear Regression Slope indicator (e.g., Chande and Kroll 1994, p. 20ff.).

[3] It should be noted that we have no direct interest in these two coefficients but only, indirectly, in the resulting estimated value $\widehat{p_t}_i$. In contrast to the former, the latter is reliable even when the regression is based on very few data points; in the extreme case (i=1) even just one – undoubtedly, p_t itself provides an adequate basis for $\widehat{p_t}_i$ (since a straight line cannot be formed from a single point, $\hat{\beta}_{t,i}$ must be manually set to 0 in (3b) for this case).

[4]The exception are "exotic" MAs that are non-linear *in the prices*, such as the Geometric Moving Average $GeoMA_n(t) = \sqrt[n]{p_t \cdot p_{t-1} \cdots p_{t-n+1}}$. However, many members of this group can be linearized.

[5]There also are two notation-only differences: First, we do not factor out $1/n$ as a normalization constant here because that would hardly make sense in general. Second, MAs are calculated from right to left while the regression lines in (1) are formed from left to right. However, this all is mathematically equivalent.

[6]In practice, there are two different approaches that trading programs can use to handle this. The approach described in the following involves calculating the EMA up to the very first available data point. Alternatively, the calculation can be stopped after exactly n steps. In that case, the coefficient of the n-th price $p_{(t-n+1)}$ must first be corrected by the factor $\frac{1}{\alpha}$. The procedure can then continue analogously to the WMA.

[7]One can sometimes find MAs under this designation that are harmonic in the prices rather than in the coefficients (and thus "exotic") (e.g., gorx1 2020); the HMA presented here should not be confused with those.

[8]For some applications, even a negative P (i.e., a "retrospective") might make sense.

[9]This observation prompts the question of whether one could also apply trend adaptation to the forecast value (instead of the actual value), effectively meaning a "second-order" kind of TAMA, similar to applying an MA to itself. This is presumably not feasible or sensible since the crucial value p_t is missing or already estimated in the forecasting scenario, but this can be a subject for further research.

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How the Deltachart Order Flow and Divergence Delta Candles Works Together to Forecast the Price Movement on High Volatile Market

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Abstract

With the technological development in all aspects of life, it was necessary to search for specific tools that search in the depth of the market and give the trader signals about the movement of smart money that drives the market. For the same concept, the most important thing about flow order and delta candles is that they show the aggregation when reaching important levels that are difficult for any other indicators to detect, especially during times of sharp volatility due to news. We will prove in this study that these tools and their combination with technical analysis are very powerful on futures market or the stock market as well we will prove this with interactive charts before and after as much as possible.

Acknowledgement

I want to thank my family, especially my lovely wife, for their continuous support during the thesis submission process. As the first Yemeni seeking to establish a name for himself in the financial markets, I am grateful for their support and faith in my endeavor. I am also grateful to my colleagues at the organization for their great assistance throughout this amazing attempt. Their assistance has been critical in achieving this goal.

INTRODUCTION

1.1 How Delta Chart Operates

Delta chart trading is a technical analysis method used by traders to evaluate asset buying and selling pressure over a period of time [1] ("What Is Volume Delta Indicator?") This strategy is based on delta volume, which refers to the difference between the buying and selling volumes at each price level.

Traders can more easily pinpoint areas of high liquidity and places where price action is expected to occur when using delta charts and Japanese candlestick patterns. Additionally, this strategy helps traders to make informed trading decisions by providing them with a clear picture of the supply and demand forces behind the price movements using Japanese Candlestick patterns.

This study aims to comprehensively examine the concept of delta chart trading and assess its effectiveness within the futures markets through the utilization of multiple live trade examples.

1.2 How Delta Chart Divergence Operates

When making decisions in trading based on volume, understanding the delta is essential [2] (Dubey)

The disparity exists in the contrasting quantities of market orders executed through the act of raising the offer price and those executed through the act of hitting the bid price. In alternative terms, when Delta exceeds zero, there was a surplus of buying than selling, whereas when Delta falls below zero, there was a surplus of selling than buying [3] ("Bar Delta & Delta Divergence")

To illustrate how delta chart divergence functions consider the following examples:

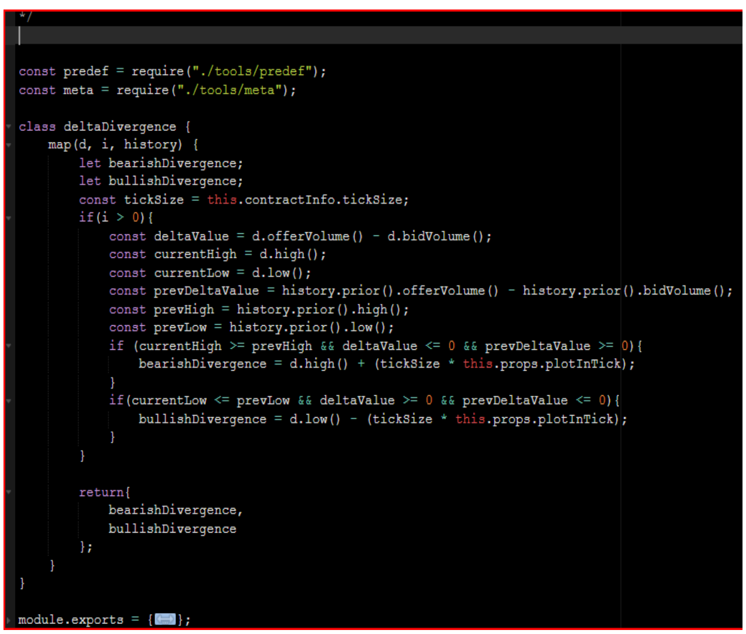
1. Bearish Divergence: Price hit a new high peak, but selling is more than buying.
2. Bullish Divergence: Price struck a new low point but buying exceeded selling.

The Plots are:

1. A red arrow above the high when price makes higher high on negative delta.
2. A Green arrow below the low when price makes lower low on positive delta.

TS Trader, which is powered by Tradovate, has this open-source formula which is presented below:

Chart 1: (Delta Candle Divergence Formula)



```
*/

const predef = require("./tools/predef");
const meta = require("./tools/meta");

class deltaDivergence {
    map(d, i, history) {
        let bearishDivergence;
        let bullishDivergence;
        const tickSize = this.contractInfo.tickSize;
        if(i > 0){
            const deltaValue = d.offerVolume() - d.bidVolume();
            const currentHigh = d.high();
            const currentLow = d.low();
            const prevDeltaValue = history.prior().offerVolume() - history.prior().bidVolume();
            const prevHigh = history.prior().high();
            const prevLow = history.prior().low();
            if (currentHigh >= prevHigh && deltaValue <= 0 && prevDeltaValue >= 0){
                bearishDivergence = d.high() + (tickSize * this.props.plotInTick);
            }
            if(currentLow <= prevLow && deltaValue >= 0 && prevDeltaValue <= 0){
                bullishDivergence = d.low() - (tickSize * this.props.plotInTick);
            }
        }

        return{
            bearishDivergence,
            bullishDivergence
        };
    }
}

module.exports = {⟺};
```

Charts can be utilized as a tool for examining the historical fluctuations in currency prices, represented graphically over a specific period. These indicators are subsequently employed to evaluate current prices and formulate forecasts regarding future price fluctuations [4] ("12-Month Japanese Candlestick Patterns")

Delta candles are widely recognized and utilized as a significant analytical instrument within financial markets, primarily employed for the purpose of predicting and projecting future price fluctuations. The candlesticks exhibit distinct components, including a body and shadows, which facilitate the recognition of bullish and bearish market conditions.

By utilizing these visual cues, traders are able to accurately identify optimal entry and exit positions within financial markets. Delta candles are regarded as a valuable instrument for individuals at all levels of trading proficiency, encompassing both novices and seasoned practitioners [4] ("12-Month Japanese Candlestick Patterns")

The body of a delta candle serves as an illustrative instance, represents the thickest section of the candlestick, and signifies the difference between the opening and closing prices. A range of patterns is utilized to indicate the formation of these candles [4] ("12-Month Japanese Candlestick Patterns")

A wide range of tools can be utilized to analyze price action in financial markets. These tools include trend lines, price channels, moving averages, Fibonacci retracement levels, Bollinger Bands, as well as technical indicators such as the Relative Strength Index (RSI), Stochastics, the Average True Range (ATR), and the MACD indicator.

There is no obvious differentiation between delta candles and Japanese candles, as both are utilized for the purpose of analyzing price action in a similar manner. Candlestick charts can be analyzed using a range of analytical tools, such as moving averages, support and resistance levels, and candlestick patterns.

The delta chart typically works:

1. Data Collection: Delta Chart collects data on trading volume and order flow at various price levels. This information can be obtained through market exchanges or through order flow software.
2. Calculation of Delta: The calculation of the Delta value involves subtracting the selling volume from the buying volume for each price level. A positive Delta denotes an increase in buying volume, while a negative Delta indicates a rise in selling volume. The Delta value serves as an indicator of the overall buying or selling pressure observed at a specific price level [5] ("Delta and Cumulative Delta: How Could They Help a Day Trader?")
3. Visualization: The graphical representation of Delta values is commonly observed on the y-axis of the chart, usually in the shape of bars or lines, while their corresponding price levels are shown on the x-axis. Each discrete bar or line on the graph represents the Delta value that is linked to a specific pricing point.
4. Color Coding: In order to enhance the process of visual interpretation, it is common practice to employ color-coded Delta bars or lines. In general, the use of green or blue colors is customary for expressing positive Delta values, which signal an inclination towards buying pressure. Conversely, red hues are traditionally employed to depict negative Delta values, indicating a propensity toward selling pressure.
5. Analysis and Interpretation: The Delta Chart is employed by traders to derive information pertaining to the disparity between buying and selling pressure at different price levels. The individuals engage in the identification and analysis of patterns, trends, and discrepancies in relation to the fluctuations in Delta and price (Chen)

- Accumulation: The presence of a significant accumulation of positive or negative Delta in specific areas can signal robust buying or selling zones, respectively. These zones may act as future support or resistance levels.
- Divergence: Divergence refers to disparities between Delta value changes and corresponding price movements, which can serve as valuable trading indicators. For instance, when prices rise but Delta decreases (showing negative divergence), it may suggest a decline in buying pressure and potential trend reversal.
- Momentum: Analyzing changes in Delta values in terms of speed and magnitude provides insights into the strength of buying or selling pressure, indicating momentum.

It is noted that Delta Charts primarily rely on order flow and volume data, and their interpretation may exhibit variability contingent upon the trader's strategy and the particular market under analysis. Furthermore, Delta Charts are frequently employed in conjunction with other technical analysis instruments to facilitate informed trading judgments.

MATERIALS AND METHODS

The researchers commence their work by formulating a comprehensive research strategy that outlines the objectives of the study, the methods of data collecting, and the analytical approaches to be employed. The initial phase involves doing a comprehensive review of the existing body of literature in order to enhance understanding of the topic and identify any areas where knowledge is lacking. Consequently, this process enables the formulation of research inquiries and hypotheses, which afterwards serve as the overarching structure for the subsequent phases of the investigation.

Following this, the researchers proceed with the gathering of data, which includes both qualitative and quantitative data. Qualitative data is obtained through conducting in-depth interviews with participants, which serves as a medium for individuals to express their experiences and perspectives regarding DELTACHART. On the other hand, quantitative data is obtained through the administration of surveys and questionnaires, facilitating the acquisition of statistical data and the quantification of distinct factors. The integration of qualitative and quantitative data is intended to provide a holistic comprehension of the impact and effectiveness of DELTACHART.

Upon obtaining the available data, the researchers utilize a range of statistical techniques and software tools to carry out a thorough investigation. The objective is to discover patterns, trends, and correlations within the dataset. The purpose of this analytical undertaking is to identify and evaluate the merits and drawbacks of DELTACHART, as well as explore its possible uses and limitations. The research results are then analyzed and presented in a comprehensive research report, which includes specific suggestions for educators, policymakers, and other stakeholders who are considering the adoption of DELTACHART in their own settings.

In summary, the technique utilized in the investigation of DELTACHART is distinguished by its rigorous and systematic precision. The process involves a thorough examination of relevant scholarly sources, followed by the gathering of data using both qualitative and quantitative methods. The data undergoes thorough examination using statistical methodologies, resulting in useful insights into the effectiveness and performance of DELTACHART. In general, this methodological approach guarantees that the study is thorough, reliable, and relevant to the requirements and concerns of educational professionals and policymakers.

2.1 Importing CME Globex Depth of Market Data

CME Globex Depth of Market Data is a data offering provided by CME Group. This product consists of all necessary market data messages for the recreation of the order book. Trade data for all products traded on CME Globex is included, as well as five to ten orders deep in futures markets and three orders deep in options markets that are provided by the Market Depth files[6] ("Market Depth - Electronic Platform Information Console - Confluence").

In order to facilitate the importation of this data, it is imperative to possess a formal clearing firm relationship with CME Group, as well as a CME Group-certified trading application and the necessary connectivity to CME Globex [7] ("Trade on CME Globex - CME Group")

CME Group data can be accessed through a variety of channels, including a network of over 300 distribution partners worldwide, as well as the proprietary market data platform and the highly regarded cloud distribution capabilities. The utilization of the CME Data Mine Market Depth files is also possible, as these files are exclusively accessible in FIX/FAST format.

In recent times, a number of service providers have emerged in the market, offering data services tailored specifically for traders. Notable examples include E-Signal, Ninjatrader, ATAS, Clusterdelta, and Volfix.

In this study, we will be utilizing the Clusterdelta data that has been imported into the Metatrader 4 platform, along with the Go Charting.

The integration of CME Globex Depth of Market (DOM) data into DeltaChart has the potential to greatly enhance the trading knowledge and understanding of both traders and others with an interest in the financial markets. The CME Globex Depth of Market (DOM) provides immediate access to bid and ask prices, as well as different contract volumes. Traders can enhance their understanding of market dynamics and make informed trading decisions by effectively integrating this data into DeltaChart, a comprehensive platform for charting and technical analysis.

The extensive functionality and tools offered by DeltaChart allow traders to analyze Depth of Market (DOM) data, hence facilitating the identification of patterns, trends, and the prevailing market sentiment. For example, individuals have the ability to closely examine the changes in the order book throughout a period of time, evaluate the levels of market liquidity, determine the strength of support and resistance levels, monitor the impact of significant orders, and identify possible turning points in the market. Trading professionals can enhance their trading methods by incorporating CME Globex DOM data into DeltaChart in a seamless manner. These tactics consider both the fluctuations in prices and the underlying complexities of the market. As a result, traders have the ability to make informed judgments that might potentially result in more profitable trades and a more comprehensive understanding of market dynamics.

CME Globex Depth data refers to the comprehensive market depth information provided by the electronic trading platform, Globex, developed by the CME Group. The information includes the most competitive bid and ask prices, along with the related order volumes at various price levels. The assessment and application of CME Globex Depth data generally encompass the subsequent stages:

1. Determine Data Requirements: Initiate the process by precisely identifying the requisite market depth data for the designated CME markets and financial instruments. CME Group provides a wide range of futures and options contracts that encompass a diversified selection of asset classes.
2. Choose a data vendor: Typically, gaining access to CME Globex Depth data requires subscribing to a data provider that supplies the requisite market data services. Prominent data vendors in the financial industry encompass Bloomberg, CQG, Refinitiv (formerly known as Thomson Reuters), and Interactive Brokers. These companies provide users with access to both real-time and historical market data, which includes detailed in-depth information.
3. Establish Data Feed Connection: Once a data source has been selected, the subsequent action involves establishing a connection to their data feed. The process often entails establishing an account, obtaining the necessary access credentials, and configuring the trading or analytical platform to establish a connection with the data feed.
4. Import and utilize the data: Once a connection has been successfully established, the next step involves importing CME Globex Depth data into your trading or analytical platform. This particular procedure may exhibit variability contingent upon the platform and data provider. In general, data can be accessed by APIs (Application Programming Interfaces) or data feed protocols such as FIX (Financial Information Exchange) or custom APIs offered by the data provider.
5. Analyze and Interpret Market Depth: The study and interpretation of market depth involve examining the imported data to gain a deeper understanding of the dynamics of supply and demand, patterns of order movement, and the levels of liquidity in the CME Globex market. The acquisition of this vital knowledge can be

utilized to make informed trading decisions or develop profitable trading strategies.

2.2 How to read Delta Chart and Delta Chart Divergence

Analyzing price movements and comparing them with the delta chart Histogram is a crucial aspect in financial analysis. This involves identifying reverse candle patterns and examining Volume Delta Divergence behavior, wherein a bullish candle is observed alongside a red delta volume indicating selling, and vice versa.

In order to proficiently comprehend and assess the divergence of a Delta Chart, it is imperative to examine the data depicted on the chart with the aim of comprehending the intricacies of buying and selling pressure dynamics.

It is imperative to underscore that the utilization of Delta Chart analysis and divergence analysis should not be regarded as independent methodologies. In order to make informed trading decisions, it is advisable to supplement them with additional technical analysis tools and indicators. Regular practice and accumulated expertise in analyzing Delta Charts and identifying divergences will improve one's ability in effectively employing these tools.

Chart 2: Entered a selling position with EURUSD (it's very clear that bullish candle reached 1.0649 with aggressive selling activity in the resistance area confirmed by Delta divergence behavior (when the candle is bullish while the delta volume is red

Proficiency in comprehending and analyzing Delta Charts and Delta Chart Divergence holds paramount significance for investors and traders seeking to make well-informed judgments inside the realm of financial markets. The Delta Chart is a graphical depiction that illustrates the relationship between the price of an option and the corresponding changes in the price of the underlying asset. The given statement effectively illustrates the manner in which the price of an option responds to fluctuations in the underlying asset, so providing valuable insights into the potential for profitability and associated risks.

The process of analyzing the Delta Chart includes evaluating both the slope and shape of the chart. A positive slope indicates that the value of the option increases in tandem with the growth in price of the underlying asset, whereas a negative slope implies a loss in value as the price of the asset increases. Steep gradients on a graph are indicative of a greater degree of price sensitivity, whereas shallower gradients suggest a lesser level of sensitivity.

The utilization of Delta Chart Divergence is advantageous in discovering discrepancies that arise between the Delta Chart and the real-time price fluctuations of the underlying asset. The analysis of these discrepancies enables traders to forecast potential fluctuations in the price of the option and the trajectory of the underlying asset. A positive divergence arises when the Delta Chart indicates a bullish attitude, while the price of the asset exhibits a contrary movement, indicating the potential for a reversal or correction. On the other hand, a negative divergence is observed when a bearish Delta Chart coincides with a bullish trend in asset prices, suggesting an imminent correction or change in market sentiment.

Proficiently examining the divergence of Delta Charts can furnish traders with a distinct edge, facilitating the identification and exploitation of lucrative prospects, while adeptly mitigating hazards in their trading pursuits.

RESULTS

3.1 Trading Delta Chart with Candle Patterns in High Volatile Market

Engaging in transactions within a market characterized by significant volatility is a considerable obstacle, requiring the implementation of advanced tactics to effectively negotiate the rapid changes in prices. One approach that can be employed involves the employment of a trading delta chart, which is a tool that provides significant insights into the relationship between an option's price and changes in the value of the underlying asset. This tool is commonly utilized by experienced traders, enabling them to make informed judgments and capitalize on chances that arise in tumultuous markets.

In order to comprehend the efficacy of utilizing trading delta charts in market situations characterized by high volatility, it is imperative to get a comprehensive understanding of the notion of delta. The symbol delta is used to represent the pace at which the price of an option varies in response to variations in the value of the underlying asset. The relationship between delta values and strike prices is visually represented through the use of a delta chart. This chart displays the delta values corresponding to different strike prices. A larger delta value signifies a more robust link between the price of the option and the price of the underlying asset. In settings typified by swift fluctuations in prices, such as markets with high volatility, delta charts serve as a valuable tool for traders to detect options that possess elevated delta values. The potential for increased market volatility may result in greater financial gains or losses for these alternatives.

The astute analysis and effective application of trading delta charts in exceedingly volatile markets are of utmost importance. Experienced traders possess the analytical acumen required to evaluate the patterns and trends depicted in the chart. The ability to identify crucial levels of support and resistance and predict possible breakout or reversal points is facilitated by analyzing past delta values. Moreover, a thorough comprehension of options pricing models and efficient risk management strategies significantly augments their ability to make prudent selections by utilizing the delta chart. Individuals who possess this intellectual groundwork are more aptly prepared to navigate the complexities of highly unstable markets and effectively optimize their trading techniques in response.

In conclusion, the utilization of a trading delta chart offers significant value in the context of market situations characterized by high volatility, enabling traders to make decisions that are better informed. Understanding the relationship between the price of an option and the value of the underlying asset, as illustrated by delta values on a chart, is crucial for exploiting opportunities in volatile markets. As a result, individuals possessing advanced cognitive abilities and a deep understanding of market dynamics are more adept at capitalizing on and maneuvering through the intricate nature of exceedingly unstable market circumstances through the utilization of trading delta charts.

The integration of Delta chart order flow trading with candlestick patterns in exceptionally volatile market conditions can provide traders with important insights into market dynamics and potential trading opportunities. Here is an explanation of the potential outcomes that can be achieved by combining these two approaches:

1. Order Flow Analysis Chart:
    a) Detecting Buying and Selling Pressure: The examination of order flow plays a crucial role in the real-time detection of buying and selling pressure by closely examining the movement of orders. The Delta chart provides a visual depiction of the disparity between buying and selling volume, serving as a graphical representation of the order flow imbalance.
    b) Validating Candlestick Patterns: The validation of candlestick patterns can be achieved by the utilization of delta chart order flow analysis. For example, when a bullish candlestick pattern arises and the Delta chart reveals a positive Delta or strong buying pressure at that particular point, it reinforces the bullish indication. The process of validation serves to enhance the trader's level of confidence in the observed candlestick pattern.
    c) Spotting Institutional Activity: The analysis of Delta chart order flow is essential in identifying instances of institutional action within the market. The impact of orders placed by major investors on price and volume is substantial, and their identification can be achieved through the examination of order flow. Cognitive ability demonstrates notable advantages in unpredictable market circumstances, wherein the participation of institutions might lead to significant changes in prices.
2. Candlestick Patterns In Volatile Markets:
    a) Reversal Patterns: Candlestick reversal patterns, such as engulfing patterns, hammers, or shooting stars, have the potential to indicate trend reversals in markets characterized by extreme volatility. When combined with Delta chart order flow research, these patterns offer additional validation and increase the probability of a successful reversal trade.
    b) Breakout Patterns: Volatile markets frequently experience breakouts from critical support or resistance levels. Candlestick breakout patterns such as breakouts from consolidation or breaches of trendlines can signify the potential continuation of the existing trend. The integration of Delta chart order flow analysis aids in the identification of robust buying or selling pressure during these breakout scenarios, bolstering trader conviction.
    c) Determining Stop Loss Levels: The determination of stop loss levels can be enhanced by the utilization of candlestick patterns in conjunction with Delta chart order flow analysis. Traders have the ability to create stop losses at levels that are less likely to be triggered by short-term market noise by watching order flow and Delta behavior around crucial support or resistance levels that have been discovered through candlestick patterns.

By integrating these two analytical methodologies, traders are endowed with enhanced capabilities to traverse the intricacies of exceedingly volatile markets, provide judicious trading judgments, and efficiently exploit chances.

3.1.1 Trading Non-Farm Payroll, CPI Index, and other major news

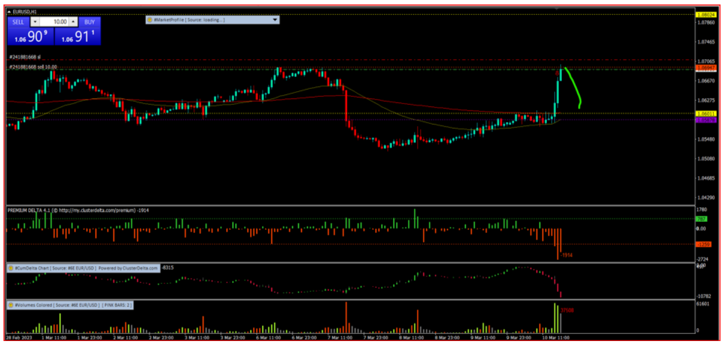
Participating in trading activities focused on non-farm payroll, CPI index, and other noteworthy news releases requires a heightened level of intellectual capacity and thorough comprehension. As a graduate-level student with a specialization in finance, I have cultivated a deep understanding of the complexities involved with economic indicators and have comprehended their potential implications on the financial markets. Staying knowledgeable and skillfully evaluating market emotion are crucial foundations for producing accurate predictions and skillfully navigating the field of trading. With a solid foundation of information and analytical abilities, engaging in the trading of significant news releases can become a powerful tool for attaining financial prosperity.

This action observed in chart (3) is evident at an early stage. Non-farm employment appeared with a total of 311,000 jobs and hit the expectations of 224,000. As a result, EURUSD experienced aggressive selling activity, reaching the resistance level of 1.06947.

This was shown by the divergence pattern on the Delta Chart, which was seen in a market that was extremely volatile as the price rapidly increased upwards and stopped at the level of resistance with a shooting star candle formation.

This would imply that traders have already begun buying USD in preparation for an upcoming increase in Non-Farm Employment, which has the potential to lead to an additional interest rate increase by the FED. The Delta Chart's divergence behavior further supports this interpretation. EUR/USD price movement between 10:00 AM and 11:00 AM is shown in this chart. The currency's price dynamics are shown by two red and green lines. Trading volume is shown by two sets of red and green bars at the chart's bottom. The stock ticker is "EUR/USD," and the current price is "1.09" in the upper left corner. The chart shows "10:00" and "11:00" in the upper right corner.

Chart 3: EUR/USD at the time touching the resistance before reversing



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The red line represents the current EUR/USD price, while the green line shows the price moving average over time. Moving averages measure short- and medium-term price movements. Prices rising above the moving average indicate an uptrend, while falling below it indicates a downturn.

Chart 4: EURUSD hit the target and drooped to 1.0635

According to chart 5, in the 15-minute chart of the Dow Jones, after January 6, 2023, the Non-Farm Payroll exceeded expectations, as 223K employment positions were reported, surpassing the market's anticipated figure of 200K.

Furthermore, the unemployment rate experienced a decline to 3.5%, instead of the anticipated rate of 3.7%. Consequently, the price experienced a rapid rise to 33302.78. It is worth noting that this upward movement was accompanied by the presence of selling positions. The confirmation of this observation was confirmed by the presence of the Delta Divergence pattern, followed by the appearance of a Doji candlestick.

The positive delta divergence in chart 6 indicates that significant market participants, or 'whales,' began to accumulate more buying contracts. Nobody expected the Dow Jones to set a new daily high. Despite this, the news caused a drop in prices.

Remarkably, the Dow Jones moved by over 700 pips in the same day, demonstrating the market's high volatility.

Chart 5: YM Futures Contract Touching Support Area

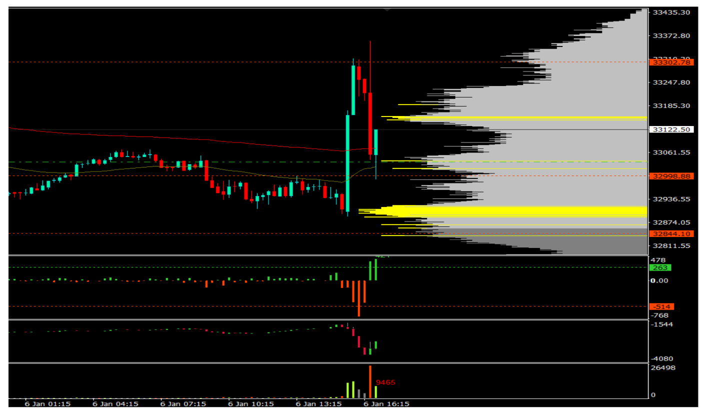


Chart 6: YM Futures reverse and changes its direction after the positive delta divergence appeared in Support Areas

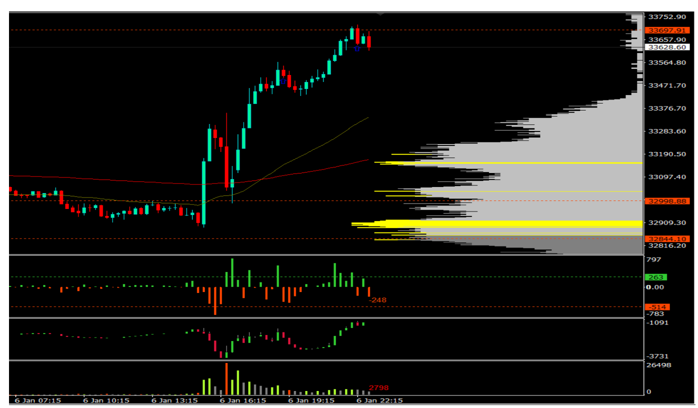


Chart (7) shows a significant crash in the Crypto market on November 4, 2022, which was further exacerbated by the shocking announcement of FTX's bankruptcy and fraudulent news. Bitcoin prices were expected to fall significantly, according to traders.

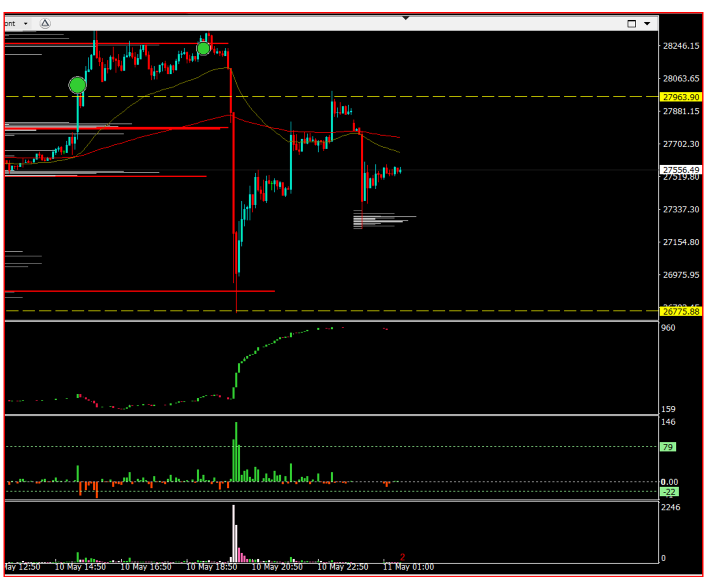
However, contrary to forecasts, aggressive buying activity increased unexpectedly. The Delta Volume Divergence verified this surprising buying, demonstrating that traders bought more Bitcoins from 15000/16000, which was contrary to traders' expectations. Notably, the positive volume was high, an occurrence that had not been seen since 2020.

Chart 7: BTC Futures Chart

The Bitcoin Futures market suffered a significant event on May 10, 2023, following the announcement of the Consumer Price Index (CPI) with complex results relating month-on-month (m/m) and year-on-year (Y/Y) data.

Chart (8) shows that the price of Bitcoin fell from 28246.15 to 26775.88 when we suddenly noticed an aggressive buying activity with Delta Volume Divergence indicating that traders bought more Bitcoins confirmed by Hammer pattern formation indicating that the market moved up against the trader's expectation from 26970 to 27963 within a few hours.

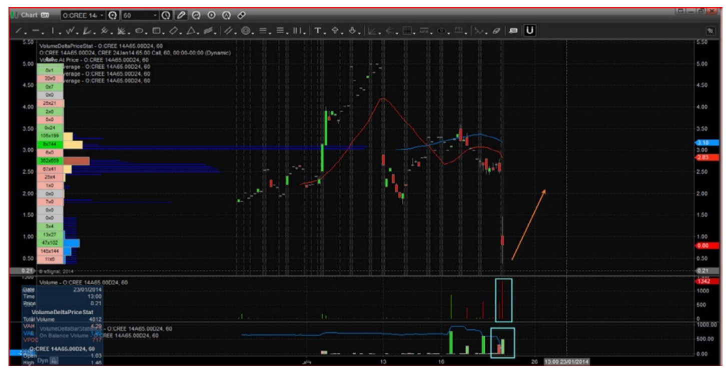
Chart 8: BTC Futures on 10th May 2023



During the CREE earnings announcement, the same observation can be made regarding both Stocks and Option Contracts. By analyzing the market depth and Delta Chart, we can determine the legitimacy of the reversal candle, which in this instance was a bottom formed Doji.

This provided investors with sufficient conviction to buy CREE stock options. The volume analysis, in particular the Orders Flow, revealed that pending buy and sell contracts were concentrated within the Doji candle at the support level. This indicates that the volume of trading for the succeeding green candle was bullish, despite the overall volume of trading being red or bearish. Notably, while options contracts initially reflected negative sentiment during the announcement decline, the presence of positive buying orders on options contracts indicated a comfortable buying sentiment emerging from the support level.

Chart 9: Cree



The chart no. 10 below demonstrates a clear reversal pattern whereby the price action demonstrates a movement contrary to that of the support area. The claim of this reversal is substantiated by the existence of a Doji candlestick pattern and a positive order flow Delta volume.

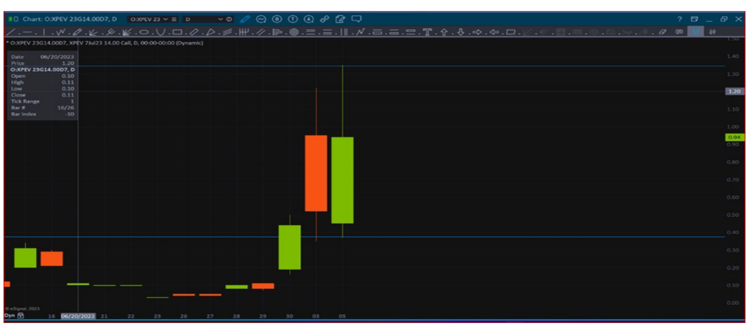
Chart 10: CREE dropped after earning released, it shows the reverse from the support area supported by Doji candle + Positive order flow Delta volume with delta divergence

According to the filing made with the Hong Kong Stock Exchange (HKEX), Morgan Stanley's ownership stake in Xpeng, a company involved in the production of electric vehicles, had a significant surge in volatility. Specifically, their long position in Hong Kong shares of Xpeng escalated to 6.13%. The aforementioned rise was substantiated by a typical trading volume observed in the option contract associated with a strike price of $14 on the 7th of July.

At the outset, traders observed that the substantial trading volume associated with a bearish candle might potentially suggest a persistence of the downward trend in prices. Nevertheless, the Delta Chart Divergence analysis indicated that the apparent increase in trading volumes was predominantly attributable to robust buying orders for the call option contract, which was initially priced at $0.42 and experienced a significant jump to $1.32.

Chart 11: XPEV 7th July.23 — Call $14 Strike

Chart 12: XPEV 7th July.23 — Call $14 Strike hit $1.30



The significance of Delta Divergence becomes evident when conducting an analysis of stocks, particularly in the case of AAPL. During a period of price drops, the Delta Candle signifies the strategic choice made by buyers to engage in the buying of stocks from the support areas. The buying behavior is additionally affirmed by the existence of a bullish Doji candlestick pattern.

Chart 13: AAPL 9 — 20 June 2023

After experiencing a notable decrease in prices after to a gap-up opening in the American market, concerns emerged regarding the possibility of a stock price collapse. The earlier apprehension increased due to the observation of a red engulfing candlestick pattern.

Nevertheless, the delta candle offered significant insights by uncovering that these downward movements were indeed accompanied by buying activity from important market participants. Consequently, there was a subsequent increase in price from 430 to 436 on the next day.

This observation not only facilitated the understanding of investor behaviors but also emphasized the impact of their buying actions in reducing the initial downward momentum.

Chart 14: NVDA 16 Jun.23

In times of uncertainty, there exist critical moments which have importance for individuals engaged in trading activities.

The comprehension of the candle's depth and the examination of the order flow are essential in determining whether these market movements signify a desire to maintain the existing trend or suggest a possible reversal. Within the context of the

SPY box, it is of utmost importance to ascertain the verification of deceptive highs and lows, as these occurrences serve as compelling evidence during periods of recovery.

The prevailing pattern is mainly supported by the existence of reversal candlestick patterns, thereby enhancing the significance of identifying these patterns in market analysis.

Chart 15: SPY 15 May – 19 June.23

3.2 Trading in Natural Volatile Market Conditions

The GBP/USD chart below exhibits an evident upward direction in price, originating from the support area. The increase in price was accompanied by the formation of a Morning Star candle pattern, which was further supported by a notable increase in aggressive buying activity. Furthermore, an occurrence of Delta Divergence was identified, characterized by the presence of bullish candles and a positive delta histogram. These incidents occurred under normal market conditions.

DISCUSSION

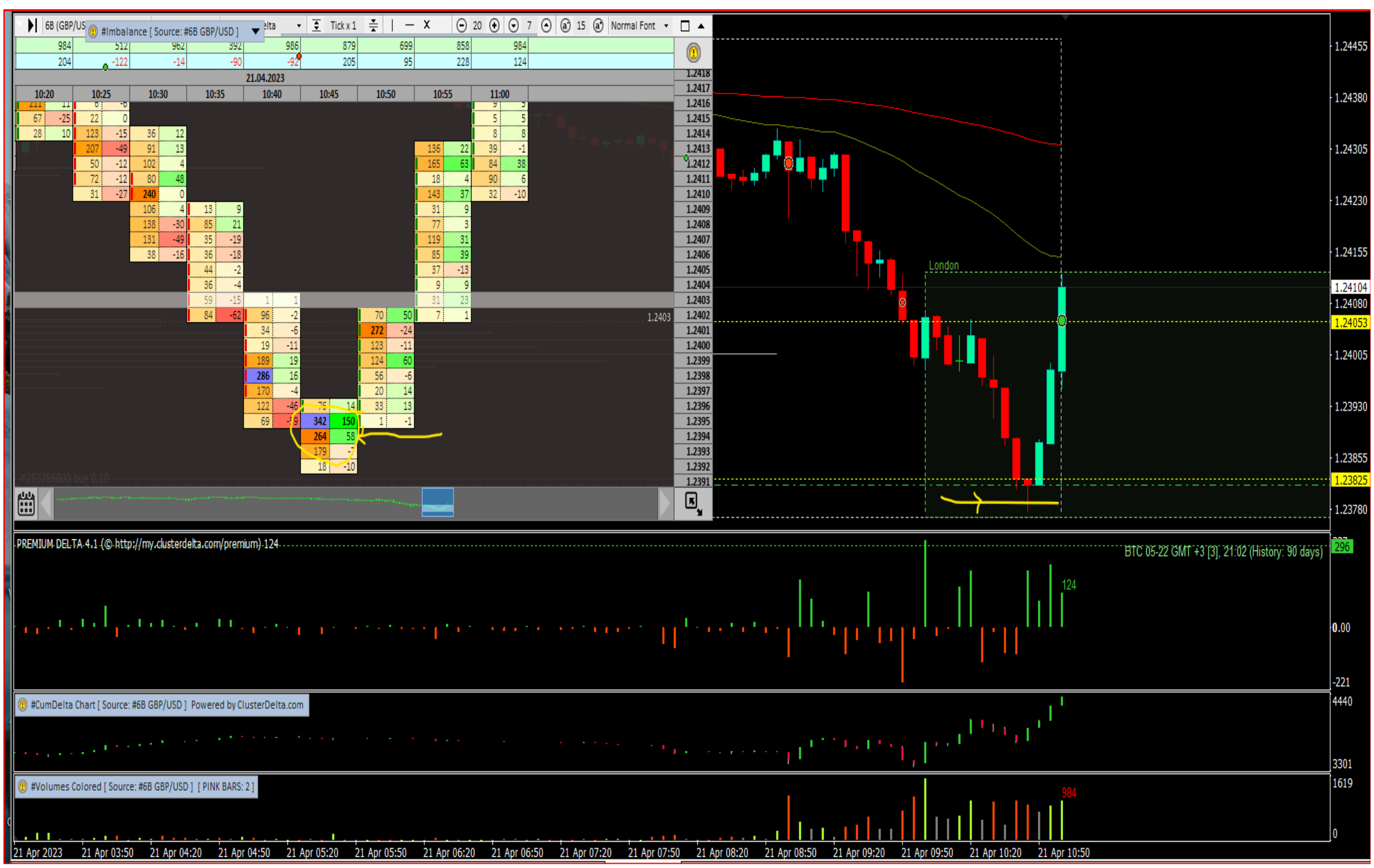
4.1 Advantages and Disadvantages of Delta Chart trading

4.1.1 Advantages of Delta Chart Trading

The utilization of delta chart trading provides numerous advantages to traders in comparison to alternative technical analysis tools.

First of all, the utilization of this tool enables individuals to observe and analyze the supply and demand forces that affect the market at any given time. The use of this approach facilitates the identification of regions characterized by higher liquidity levels, as well as the identification of potential levels of support and resistance.

Chart 16: GBP/USD 21st April 2023



The second advantage to consider is that the utilization of delta chart trading enables traders to enhance their decision-making process by providing them with a clearer picture of market trends and potential reversal points.

Furthermore, one notable advantage of using the delta chart trading methodology is its effectiveness across different market conditions. In order to effectively analyze price action and execute profitable trades, traders have the option to employ delta charts, regardless of whether the market is exhibiting a trending or consolidating behavior.

Finally, delta chart trading can be applied to different asset classes, including stocks, futures, options, and currencies.

4.1.2 Disadvantages of Delta Chart Trading

While delta chart trading offers numerous advantages, it is important for traders to be aware of the drawbacks associated with Delta Chart Trading.

Firstly, one of the primary drawbacks is that it is challenging to accurately interpret the delta values. In order to effectively employ this strategy, traders must possess an in-depth understanding of the market dynamics and the various factors that influence the delta values.

The second disadvantage to consider is that delta values can fluctuate rapidly, making it challenging to keep up with market shifts.

Lastly, one additional drawback associated with delta chart trading is its limited ability to offer a comprehensive depiction of market dynamics. While it effectively displays the buying and selling pressures associated with different price levels, it does not consider the overall market sentiment, news events, or fundamental analysis. In order to obtain a comprehensive understanding of market conditions, traders are required to utilize additional tools in conjunction with delta charts.

4.1.3 Which is better Delta Chart Candles analysis or Trading Japanese candles on Support and Resistance levels

Both the Delta Chart Candles analysis and the Trading Japanese candlesticks on Support and Resistance levels techniques utilize candlestick patterns to identify trading opportunities by examining volume and price movements.

Both the Delta Chart Candles analysis and the Trading Japanese candles on Support and Resistance levels techniques utilize candlestick patterns to identify trading opportunities by examining volume and price movements. However, these techniques for trading possess distinct merits and drawbacks reliant upon the market conditions, the time frame, and the trader's preferences [8] ("CVD - Cumulative Volume Delta Candles — Indicator by TradingView")

The analysis of Delta Chart Candles involves the utilization of intra-bar information in order to acquire volume delta information that is more accurate compared to approaches that solely rely on the timeframe of the chart.

The volume delta refers to the disparity between the volumes of upward and downward movements within a bar, serving as an approximation of the level of buying or selling activity exerted on an instrument. This methodology has the potential to assist traders in identifying divergences, reversals, breakouts, and trends based on volume activity *(9)* ("TradingView — Track All Markets")

Trading Japanese candles on Support and Resistance levels uses candlestick patterns with support and resistance levels to make sound trading decisions. Support and resistance levels are areas where buyers and sellers have set up defenses and where prices may shift direction. Candlestick patterns can assist traders in confirming or anticipating these movements, allowing them to enter or exit transactions accordingly.

CONCLUSION

The utilization of delta chart trading as a technical analysis instrument holds significant value for traders, as it enables them to assess the levels of buying and selling pressure of an asset. This approach facilitates the identification of regions characterized by substantial liquidity and the possibility of encountering potential support and resistance levels. By providing valuable perspectives on the dynamics of supply and demand that influence fluctuations in prices, it enables traders to make informed and rational choices.

However, the successful application of delta chart trading requires a thorough comprehension of the fundamental market dynamics and the various factors that influence delta values. In addition, it is recommended to integrate delta charts with supplementary tools such as candle patterns, volume analysis, fundamental analysis, and market sentiment indicators in order to obtain a comprehensive understanding of the market. Incorporating delta chart trading has the potential to enhance traders' decision-making processes and improve profitability within financial markets.

5.1 Improving the Trend direction with imbalance areas (Future Improvements)

The Imbalance indicator from Cluster Delta is specifically designed to emphasize trade imbalances that occur during the trading process. Imbalances commonly arise when there exists a substantial disparity in the ratio between buyers and sellers, such as a ratio exceeding 3 to 1 or 4 to 1 in either direction or when one side is entirely absent. This indicator effectively demonstrates various imbalances, such as the ratio of buyers to sellers within a specific price range and market imbalances where the Ask price consistently surpasses the Bid price.

The presence of imbalances is readily apparent on cluster charts, and this particular indicator enhances their visual representation on price charts.

The ability to interpret imbalances in buying orders and selling offers is essential for validating the analysis of order flow and the delta chart. The provided statement effectively identifies the specific points of entry that lead to an imbalance between the supply and demand within a given candlestick.

Furthermore, the recurrence of these imbalances at close price levels serves as an indication of successive transactions carried out by substantial market participants, thereby supporting the strength of the trend in either buying or selling. The identification of imbalances and the assessment of the persistence of buying or selling trends can be efficiently achieved by employing Footprint and Order Flow analysis techniques.

Chart 17: GC 16th June 2023

The presence of both positive and negative signals in the trend, as validated by the analysis of Order Flow and Delta charts, revealed clear price imbalances in gold upon encountering resistance levels. The observed disparities unveiled the aggressive behavior of important market participants, commonly referred to as "whales," and their clustering in particular regions and locations where deals were conducted. The price promptly reverted to these regions, implying their importance as levels that large investors would probably uphold when making the decision to sell.

This was obvious in the provided illustration of the gold chart. After encountering resistance at the 1967 level, the price experienced a subsequent decrease. Significantly, upon reaching the identical level on the minute chart, the price encountered a pronounced downward rebound. The observed behavior, in conjunction with the observed price imbalance, serves as evidence of the dominant selling pressure in contrast to the relatively weaker buying orders. This can be attributed to the encounter of a critical price resistance area that affects the direction of gold.

Chart 18: GC Dropped on 16th June 2023

As the price of gold fell below the level of 2014, the presence of selling pressure became apparent, even though the delta chart order lacked clarity.

The market makers' decision to lower the price was confirmed by the consistent execution of consecutive selling deals, as well as the imbalances observed following minimal buying activity.

All subsequent activities to return the price level from 2014 to 2012 were unsuccessful, as resistance zones promptly formed. This further confirms the existence of substantial selling orders within those regions.

The observation of price imbalances can yield valuable insights into investor behavior, informing subsequent buying or selling decisions. This finding instills a sense of assurance regarding the strength of the observed trend.

The provided chart below depicts the consistent upward movement of gold, despite occasional instances of corrective movements. Nevertheless, these corrections can be interpreted as a strategic move by market makers to strengthen their buying orders and consequently increase the price.

Chart 19: GC hit target on 16th June 2023

Enhancing the precision of market direction determination through imbalance areas could benefit from several strategic considerations:

1. Finesse Imbalance Area Analysis: The focus is on continuously refining and improving the existing approach to ensure more accurate and comprehensive results. This study aims to explore alternate methodologies for accurately detecting and delineating these regions by considering the inclusion of particular volume thresholds or corroborating imbalances with other technical indicators.
2. Incorporate Multiple Timeframes: Utilize a multi-timeframe methodology while conducting an analysis of areas of imbalance. Evaluating the alignment of these regions across different timeframes might offer a more thorough perspective on the overall market trend and prospective trading prospects.
3. Cross-Validation with Other Techniques: Cross-validation in conjunction with other analytical techniques can be employed to validate and corroborate findings related to regions of imbalance and market direction. The

incorporation of imbalance area analysis into market assessments, when combined with supplementary technical analysis tools such as trendlines, chart patterns, or oscillators, has the potential to strengthen evaluations of market direction and enhance trading decisions.

4. Leverage Volume Profile Analysis: Utilize the technique of volume profile analysis to gain a more comprehensive understanding of volume distribution within areas of imbalance. The identification of significant volume clusters can provide further confirmation of support or resistance levels and aid traders in assessing the intensity of market imbalances.
5. Back testing and Data Examination: Conduct comprehensive back testing and data analysis to verify the effectiveness of imbalance areas in forecasting market trends. By doing an analysis of historical data and conducting a comparative examination of trade outcomes in relation to regions of imbalance, traders can enhance their strategies and identify any recurrent patterns or biases that may impact market trends.
6. Continuous Learning and Adaptation: Continuous learning and adaptation are essential for individuals to remain up to date with the latest advances and innovations in the field of market analysis. Participate in workshops, webinars, or educational courses to enhance one's knowledge in the field of imbalance area analysis and its potential for determining market trends.

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ENDNOTES

(1) This source provides insights into the Volume Delta indicator and its application in trading.

(2) This is a GitHub repository maintained by Sanjay Dubey, containing custom trading indicators for the Tradovate platform.

(3) This source explains the concepts of Bar Delta and Delta Divergence in the context of order flow trading.

(4) This source discusses 12-month Japanese candlestick patterns in the context of forex trading.

(5) This source explores the benefits of using Delta and Cumulative Delta indicators for day trading.

(6) This source provides information related to market depth on the CME Group's electronic platform.

(7) This source explains the process of trading on the CME Globex platform, operated by CME Group.

(8) This source introduces the Cumulative Volume Delta (CVD) indicator available on the TradingView platform.

(9) TradingView is a versatile platform for tracking various financial markets and related data.

Using Renko Charts for Noise Reduction and Directional Insights in the US Equity Market:

A Multi-Dimensional Approach Integrating Investment Factors, Sector Analysis, and Volatility Filters

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Abstract

This thesis introduces a multi-dimensional trading methodology that intertwines Renko chart patterns, volatility expectations, and financial ratios. We present a unique approach to segmenting implied volatility into distinct contexts and assessing three strategic components: segments of market conditions, investment factor strategies, and sector trend strategies. This methodology is articulated through in-depth discussions on bullish and bearish positioning rules, selection of Renko patterns, exit strategies, and considerations of exposure.

A key innovation is the Renko Directional Z-score (RDZ), a quantitative measure that extends beyond traditional visual analysis by objectively quantifying trend strength and momentum. The RDZ has multiple applications, notably in identifying overbought and oversold conditions. Building on this, we introduce the Leading RDZ, a cutting-edge market breadth indicator engineered to respond to future volatility expectations by incorporating the VIX term structure.

Our approach offers a dynamic and adaptable framework for trading operations, empowering traditional Renko chart analysis with a dimension of forecasting market volatility, a layer of financial ratios, and a statistical perspective. While this empirical research is exclusively focused on the U.S. equity market, it acknowledges the inherent limitations of historical backtesting and the influence of external factors beyond our predictive capacity. The study not only provides a practical and versatile trading compass for navigating diverse market landscapes but also lays the groundwork for future research. This opens avenues for the evaluation of this methodology in other financial markets and the exciting potential incorporation of cutting-edge data analytics, neural networks, and revolutionary AI.

1. INTRODUCTION

The global financial crisis of 2008, the more recent COVID-19-induced market turmoil, and the ongoing conflict in Eastern Europe emphasize the formidable challenge of navigating the volatile U.S. equity market. Geopolitical events, inflation shifts, and interest rate dynamics introduce intricacy, complexity, and uncertainty, leaving investors grappling with the identification of trends and directional opportunities.

Traditional technical analysis tools like moving averages and oscillators sometimes prove insufficient in filtering out market noise, leading to misleading signals and contradictory predictions. Their reliance on fixed time intervals can fail to capture the market's true dynamism. This is where Renko charts step in, a type of price charting method that factors in price changes but not time. By offering a time-agnostic visualization, Renko charts excel in highlighting market trends by reducing noise and presenting more discernible and less subjective chart patterns.

Despite their utility, the application of Renko charts remains largely uncharted territory in existing literature and market practices. This paper seeks to fill this gap by investigating how Renko charts, when combined with other analytic tools, can enhance directional insights in the U.S. equity market. To achieve this objective, we strive to construct a holistic approach that intertwines market filtering mechanisms using the VIX term structure and Treasury yields, a comprehensive sector trend and relative strength analysis, and factor investing strategies.

The paper unfolds as follows. We begin with a brief literature review covering the essential elements of our study, followed by a detailed exposition of our backtesting methodology and data modeling. Subsequently, we present the results of our empirical research, focusing on the performance of long/short Renko patterns, optimizing Renko performance with market condition filtering, and identifying optimal investment strategies across various volatility contexts. We conclude by unveiling a methodology anchored in our findings, introducing two pioneering indicators centered on Renko charts and volatility, and acknowledging limitations while outlining potential paths for future research.

Through this exciting exploration, our aim is to provide a multi-dimensional compass for guiding traders' decision-making processes and to contribute meaningfully to the existing body of literature on technical analysis, particularly focusing on the integration of Renko chart patterns within diverse volatility contexts.

2. BRIEF LITERATURE REVIEW

2.1. Construction and Relevance of Renko Charts

The basis of Renko charts is price movement, not time intervals. Each brick on a Renko chart represents a specific price increment, or the “box size”. This could be a fixed price increment, or one dynamically calculated using the Average True Range (ATR), a method that adjusts the brick size in line with recent price movements (Wilder, 1978). Renko charts simplify trend analysis by eliminating minor price fluctuations and the time factor, creating an unambiguous representation of price trends. These charts clearly visualize support and resistance levels and can be used alongside other technical indicators for a comprehensive market view. However, Renko charts may not fit time-centric strategies, work less effectively in range-bound markets, and are inefficient when tracking prices gaps (Dawson & Steenbarger, 2021). Their box-size determination, subjectively set, requires careful adjustment to accurately reflect market dynamics and prevent overlooking significant trends or creating excess noise (Smith, 2020). The effectiveness of Renko charts has been documented by research papers conducted by Bernal and Venegas-Martinez (2018), Yang and Su (2019), and Zhang and Ma (2020).

Figure 1. Price chart and ATR

Figure 2. Renko chart with ascending triangle breakout

2.2. VIX Index and Its Term Structure

Often referred to as the "fear index", the VIX Index gauges market volatility and is derived from S&P 500 index option prices (Whaley, 1993). The term structure of the VIX index, which illustrates the relationship between the prices of VIX futures contracts with multiple maturities, can be a powerful tool for forecasting upcoming market volatility and risk sentiment. However, its predictive capacity might decrease during periods of market uncertainty or following major economic events like the 2008 Financial Crisis (Engle & Rangel, 2008). This has been demonstrated in studies, such as those conducted by Cao, Wei, and Zhong (2015) and Alizadeh, Brandt, and Diebold (2002).

2.3. US Treasury Yield Curve

Over time, the US Treasury yield curve - especially its inversion, where short-term rates surpass long-term ones - has acted as a predictor for upcoming economic recessions (Estrella and Mishkin, 1998). Adrian and Wu (2019) employed machine learning techniques to confirm the predictive power of yield curve shape changes, including the role of the yield curve slope and its curvature. Changes in the yield curve can also impact risk sentiment and asset prices.

2.4. Common Investment Factors

Factors such as size, value, quality, momentum, and risk volatility are commonly utilized in the investment sector to create extra returns (Fama and French, 1993; Asness et al., 2013). However, their effectiveness may fluctuate across market cycles, igniting spirited discussions and debates. For instance, the value factor might underperform during periods of economic expansion but could outperform during economic downturns (Baker et al., 2011).

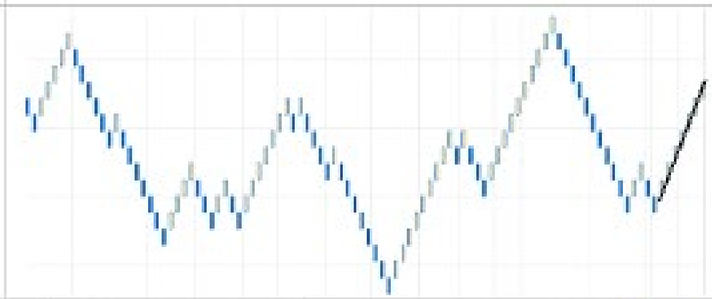
2.5. Top-Down Sector Analysis

The approach of top-down sector analysis - evaluating macroeconomic data and sector performance to pinpoint trends and opportunities - has proven effective in generating superior returns (Sharpe, 1992; Lin and Sun, 2019). Combining sector analysis with other investment factors, such as momentum and value, can further enhance investment strategies. However, we must consider the risks associated with inaccurate macroeconomic forecasts and unforeseen events. Potential improvements might involve diversifying across sectors and integrating bottom-up stock picking with the top-down approach (Arnott & Bernstein, 2002).

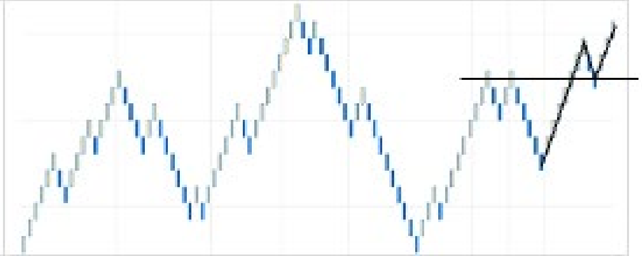
3. BACKTESTING METHODOLOGY AND DATA MODELING

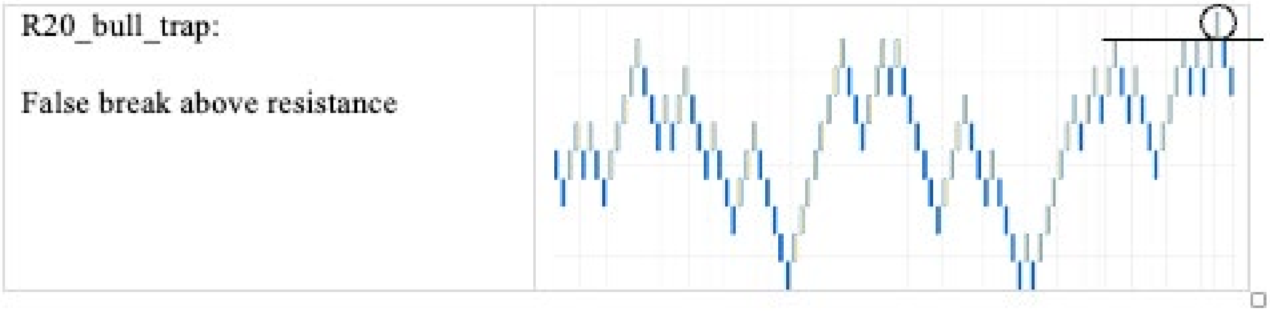
3.1. Identifying Twenty Renko Chart Patterns

Figure 3. Selecting Bullish and Bearish Renko patterns

RENKO PATTERN	VISUALIZATION
R1_white_trend: 5+ boxes increase	
R2_black_trend: 5+ boxes decrease	
R3_new_white: Bullish color shift	
R4_new_black: Bearish color shift	
R5_double_bottom: Breakout from 2 bottoms	

R6_double_top: Breakout from 2 tops	
R7_triple_bottom: Breakout from 3 bottoms	
R8_triple_top: Breakout from 3 tops	
R9_head_and_shoulders: Breakout from peak between 2 shoulders	
R10_inverted_head_and_shoulders: Breakout form valley between 2 shoulders	
R11_ascending_triangle_breakout: Breakout from ascending triangle	
R12_descending_triangle_breakout: Breakout from descending triangle	

R13_bullish_catapult: Bullish breakout and pullback	
R14_bearish_catapult: Bearish breakout and pullback	
R15_symmetrical_triangle_bullish_b reakout: Bullish breakout from symmetrical triangle	
R16_symmetrical_triangle_bearish_b reakout: Bearish breakout from symmetrical triangle	
R17_long_tail_down_reversal: 20+ boxes drop then recovery	
R18_long_tail_up_reversal: 20+ boxes rise then fallback	
R19_bear_trap: False break below support	



3.2. Market Filtering Conditions: Defining Ten Segments

In the following specifications, EMA(ticker,5) represents the 5-day exponential moving average. The terms 50-SMA and 200-SMA designate the 50-day and 200-day simple moving averages, respectively.

3.2.1. Four Segments for VIX Filtering Analysis

- Fear and Market Volatility Expectations:
  - Segment V1: VIX<19
  - Segment V2: VIX>24
- VIX Term Structure Contango or Backwardation:
  - Segment V3: EMA(VIX3M,5)/EMA(VIX,5)>1.1 (contango context)
  - Segment V4: EMA(VIX3M,5)/EMA(VIX,5)<1 (backwardation context)

3.2.2. Six Segments for US Treasury Yield Filtering Analysis

TNX is a widely recognized ETF used to measure the yield of benchmark 10-year Treasury notes, while TYX is an analogous ETF for 30-year Treasury bonds.

- U.S. Economy Health and Interest Rate Trends:
  - Segment Y1: EMA(TNX,5) below EMA(TNX,200)
  - Segment Y2: EMA(TNX,5) above EMA(TNX,200)
  - Segment Y3: EMA(TNX,5) below EMA(TNX,50)
  - Segment Y4: EMA(TNX,5) above EMA(TNX,50)
- Yield Curve Slope, an Indicator of Economic Expansion or Recession:
  - Segment Y5: EMA(TYX,5)/EMA(TNX,5)>1.5 (very steep yield curve)
  - Segment Y6: EMA(TYX,5)/EMA(TNX,5)<1 (relatively flat yield curve)

3.3. Specific Filtering Strategies: Defining Ten Segments

3.3.1. Six Segments for Factor Investing Analysis

Four key investment factors are considered: size, value, quality, and momentum.

- Size:
  - Segment F1: small caps with capitalization of up to $2 billion
  - Segment F2: big caps with capitalization of more than $10 billion
- Value:

Our focus is on companies that seem undervalued, as suggested by their price-to-book and current ratios.

  - Segment F3: price_book_ratio>0 AND price_book_ratio<2 AND price_cash_ratio>0 AND price_cash_ratio<20 AND current_ratio>1 AND current_ratio<40
- Quality:

We target firms with consistent capital returns over recent years and relatively lower debt profiles compared to their industry counterparts.

  - Segment F4: ROE_5-year_average>15 AND ROI_5-year_average>15 AND Debt/Equity_to_Industry<100%
- Momentum:

The common guideline is that the trend continues until substantial evidence indicates a shift. We characterize an intermediate bullish trend as: [stock_above_50-SMA] AND [13-week_relative_strength_above_50%]. A 13-week relative strength exceeding 50% implies that the stock has outperformed 50% of its exchange-listed counterparts in the past 13 weeks, or about 3 months. An intermediate bearish trend can be similarly defined as: [stock_below_50-SMA] AND [13-week_relative_strength_below_50%].

  - Segment F5: bullish intermediate trend on the stock
  - Segment F6: bearish intermediate trend on the stock

3.3.2. Four Segments for Sector Trend and Relative Strength Analysis

- Sector Primary Trend (Medium to Long Term Trend):

In analyzing any given stock, one should refer to its corresponding sector-based ETF. A primary bullish trend is defined as: [ETF_above_200-SMA] AND [ETF_26-week_relative_strength_above_50%] (26 weeks ≈ 6 months). Similarly, a primary bearish trend is characterized as: [ETF_below_200-SMA] AND [ETF_26-week_relative_strength_below_50%].

  - Segment S1: bullish primary trend on the corresponding sector-based ETF

- Segment S2: bearish primary trend on the corresponding sector-based ETF
- Sector Intermediate Trend (Short Term Trend):

In analyzing any given stock, one should refer to its corresponding sector-based ETF. A bullish intermediate trend is defined as: [ETF_above_50-SMA] AND [ETF_13-week_relative_strength_above_50%] (approximately 3 months). Similarly, an intermediate bearish trend is characterized as: [ETF_below_50-SMA] AND [ETF_13-week_relative_strength_below_50%].

- Segment S3: bullish intermediate trend on its corresponding sector-based ETF
- Segment S4: bearish intermediate trend on its corresponding sector-based ETF

3.4. Backtesting Methodology, Data Modeling and Performance Metrics

3.4.1. Data Source and Stock Universe

Data is sourced from the MarketInOut Stock screener (marketinout.com), chosen for its comprehensive coverage of market data. This platform's Formula Screener tool allows for creating expressions to identify instruments matching specific investment criteria. The Strategy Backtest tool assists in evaluating strategies against historical data and exporting the resulting data into CSV files for further analysis.

The criteria for defining the stock universe Ω are:

- Exchange: NYSE, NASDAQ
- Capitalization: Large-cap, Mid-cap, Small-cap
- Security Type: Stock
- Price Is Greater Than 10

3.4.2. Constructing and Executing the Backtesting Procedure

- Renko Tactical Strategies:

Our methodology spans from January 1, 2000, to April 30, 2023. For each of the 20 predefined Renko patterns within the stock universe Ω, we perform the following steps:

- Run 20 backtests with a long position, a 5-ATR trailing stop and a 5-ATR take profit
- Run 20 backtests with a long position and a 5-ATR trailing stop
- Run 20 backtests with a short position, a 5-ATR trailing stop and a 5-ATR take profit
- Run 20 backtests with a short position and a 5-ATR trailing stop

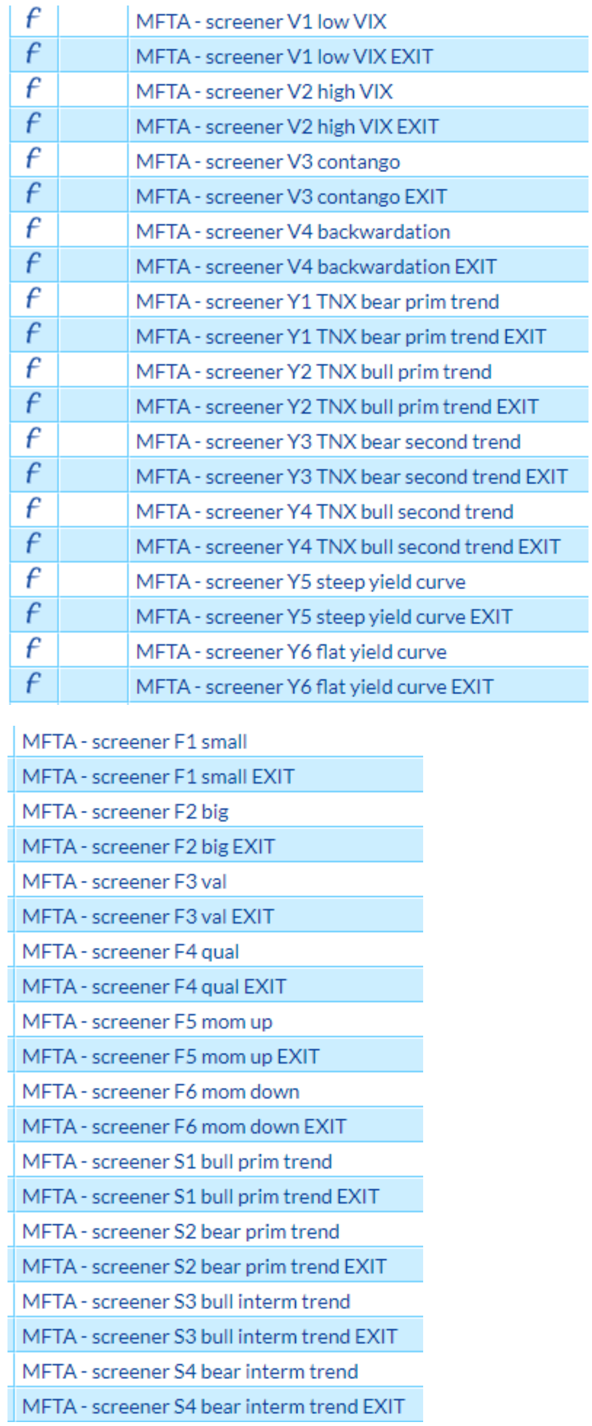
In the Strategy Backtest tool of MarketInOut, the portfolio size cap is set at 500, a limit that was not exceeded in our testing. The order execution model is based on closing prices.

- Market and Specific Filtering Strategies:

We develop stock screeners for each of the twenty predefined filtering segments: {V1,V2,V3,V4} + {Y1,Y2,Y3,Y4,Y5,Y6} + {F1,F2,F3,F4,F5,F6} + {S1,S2,S3,S4}.

Exit stock screeners are also established, incorporating a “Not” function into their expressions. These screeners form the foundation for market filtering strategies, with the original screener being used to initiate positions and the exit screeners to close them.

Figure 4. Establishing screeners in MarketInOut



Screen Name:

MFTA - screener S2 bear prim trend EXIT

Formula Expression:

```
!(
exch(nyse,nasdaq) and caps(large,mid,small) and type(stock) and last > 10
and
(
( sector(energy) and (ema(3) < ema(200))@xle and (rs126 < 50)@xle )
or
( sector(basic_materials) and (ema(3) < ema(200))@xlb and (rs126 < 50)@xlb )
or
( sector(industrials) and (ema(3) < ema(200))@xli and (rs126 < 50)@xli )
or
( sector(consumer_defensive) and (ema(3) < ema(200))@xlp and (rs126 < 50)@xlp )
or
( sector(consumer_cyclical) and (ema(3) < ema(200))@xly and (rs126 < 50)@xly )
or
( sector(healthcare) and (ema(3) < ema(200))@xlv and (rs126 < 50)@xlv )
or
( sector(financial_services) and (ema(3) < ema(200))@xlf and (rs126 < 50)@xlf )
or
( sector(technology) and (ema(3) < ema(200))@xlk and (rs126 < 50)@xlk )
or
( sector(communication_services) and (ema(3) < ema(200))@xlc and (rs126 < 50)@xlc )
or
( sector(utilities) and (ema(3) < ema(200))@xlu and (rs126 < 50)@xlu )
or
( sector(real_estate) and (ema(3) < ema(200))@xlre and (rs126 < 50)@xlre )
)
)
```

The results are exported into CSV files, presenting a data structure as follows:

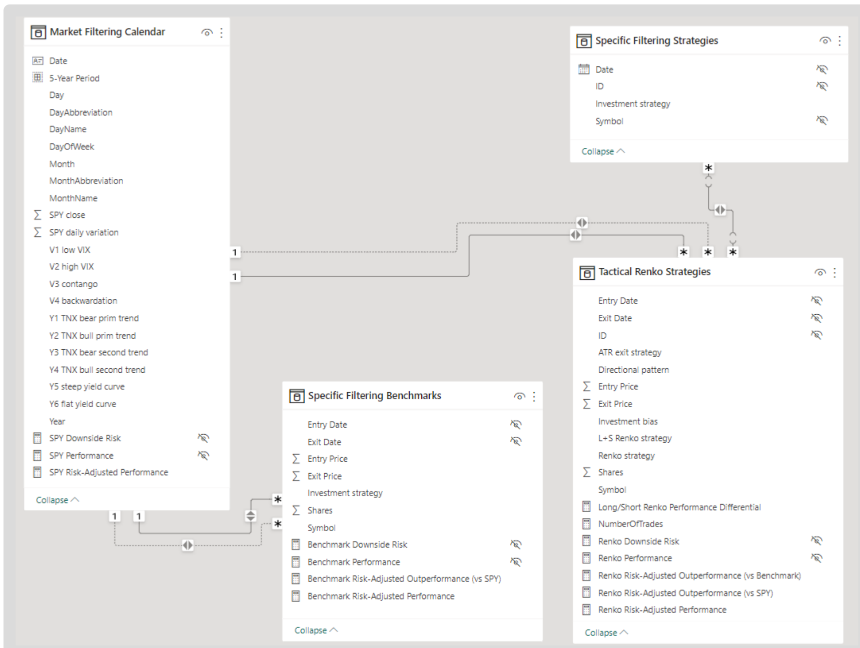
Figure 5. CSV structure of screener results

Symbol	Entry Date	Entry Price, $	Exit Date	Exit Price, $	Shares	Profit, $	Exit On	MI [?]
NOG	06/30/2023	34.32	07/03/2023	34.35	61	1.83	Period End	•
MEDP	06/28/2023	229.09	07/03/2023	239.04	9	89.55	Period End	•
UHS	06/27/2023	156.37	07/03/2023	155.41	13	-12.48	Period End	•
ESLT	06/22/2023	209.23	07/03/2023	213.78	10	45.50	Period End	•
JPM	06/16/2023	143.26	07/03/2023	146.61	14	46.90	Period End	•
BPMC	06/16/2023	61.31	07/03/2023	62.91	34	54.40	Period End	•
FTNT	06/15/2023	73.59	07/03/2023	74.66	28	29.96	Period End	•
ISRG	06/14/2023	323.07	07/03/2023	336.03	6	77.76	Period End	•
APLS	06/13/2023	93.31	07/03/2023	89.22	22	-89.98	Period End	•
CMPR	06/13/2023	54.32	07/03/2023	58.70	39	170.82	Period End	•
GWW	06/08/2023	704.98	06/27/2023	771.20	3	198.67	Take Profit	•
SIBN	06/06/2023	27.67	07/03/2023	27.28	76	-29.64	Period End	•
BZH	06/06/2023	22.52	06/28/2023	26.43	94	367.60	Take Profit	•
BMEA	06/06/2023	38.24	06/23/2023	32.08	55	-338.77	Stop Loss	•
THC	06/02/2023	74.58	06/14/2023	84.93	28	289.87	Take Profit	•
STK	05/17/2023	27.30	05/30/2023	29.63	77	179.54	Take Profit	•
XPEL	05/10/2023	76.01	07/03/2023	83.99	27	215.46	Period End	•
VRNA	05/10/2023	23.43	07/03/2023	20.13	90	-297.00	Period End	•
AMZN	05/10/2023	110.19	06/02/2023	125.58	19	292.40	Take Profit	•
HMC	05/10/2023	27.02	05/25/2023	28.77	78	136.88	Take Profit	•
MLTX	05/08/2023	27.06	06/26/2023	50.51	78	1,829.10	Take Profit	•
AQUA	05/05/2023	51.52	05/23/2023	49.88	41	-67.24	Period End	•
WRLD	05/04/2023	102.71	06/14/2023	129.22	20	530.30	Take Profit	•
VNT	05/04/2023	27.39	06/07/2023	30.81	77	263.00	Take Profit	•
GPK	05/03/2023	25.00	06/21/2023	24.49	84	-42.84	Stop Loss	•
OLLI	04/19/2023	63.18	05/25/2023	57.12	33	-200.01	Stop Loss	•
LAUR	04/14/2023	12.04	07/03/2023	12.05	176	1.76	Period End	•
PCH	04/10/2023	49.16	07/03/2023	52.81	43	156.95	Period End	•
MACK	04/06/2023	12.51	07/03/2023	12.29	169	-37.18	Period End	•

The collected data then undergoes an ETL (Extraction, Transformation, and Loading) process, for which we use the Microsoft Power Query Editor to manage data from the CSV sources. The objective is to create a unique entry for each stock on each distinct day that meets our predefined criteria. As a result, if a filter applied to the table returns a row corresponding to a specific date and stock, it implies that the stock was included in the corresponding screener on that date. Subsequently, we construct a relational data model and develop metrics to measure performance and risk. This process enables the investigation of factors that have consistently influenced outcomes over the 23-year study.

3.4.3. Creating the Power BI Data Model

Figure 6. Microsoft Power BI data model



3.4.4. Implementing Performance and Risk Metrics

We seek to identify statistically significant segments by optimizing a Renko risk-adjusted performance metric. These metrics are developed using DAX language within the Power BI data model. While our focus here is on the implementation for Renko trades, the underlying logic is also applied to SPY and the investment benchmarks incorporated in this model.

Figure 7. Renko performance and risk DAX measures

```
Renko Performance =
VAR ExitDateEval = CALCULATE(
    SUMX(
        'Tactical Renko Strategies',
        'Tactical Renko Strategies'[Shares] * ( 'Tactical Renko Strategies'[Exit Price] - 'Tactical Renko Strategies'
[Entry Price] ) * SWITCH( 'Tactical Renko Strategies'[Investment bias], "LONG", 1, "SHORT", -1, 0)
    ),
    USERELATIONSHIP('Tactical Renko Strategies'[Exit Date], 'Market Filtering Calendar'[Date])
)
RETURN
ExitDateEval
```

```
Renko Downside Risk =
//As standard deviation is not feasible due to computational resources, using the negative variations of the portfolio divided by the portfolio value is a reasonable alternative to calculate volatility. This measure is often referred to as downside risk.
VAR Risk = CALCULATE(
    SUMX(
        'Tactical Renko Strategies',
        SWITCH( TRUE(),
            AND( 'Tactical Renko Strategies'[Investment bias] = "LONG", 'Tactical Renko Strategies'[Exit Price] - 'Tactical Renko Strategies'[Entry Price] < 0 ),
            ABS( 'Tactical Renko Strategies'[Shares] * ( 'Tactical Renko Strategies'[Exit Price] - 'Tactical Renko Strategies'[Entry Price] ) ),
            AND( 'Tactical Renko Strategies'[Investment bias] = "SHORT", 'Tactical Renko Strategies'[Exit Price] - 'Tactical Renko Strategies'[Entry Price] > 0 ),
            ABS( 'Tactical Renko Strategies'[Shares] * ( 'Tactical Renko Strategies'[Exit Price] - 'Tactical Renko Strategies'[Entry Price] ) ),
            0
        )
    ),
    USERELATIONSHIP('Tactical Renko Strategies'[Exit Date], 'Market Filtering Calendar'[Date])
)
RETURN
Risk
```

```
Renko Risk-Adjusted Performance =
Divide(
    [Renko Performance],
    [Renko Downside Risk],
    0
)
```

```
Renko Risk-Adjusted Outperformance (vs SPY) =
    DIVIDE(
        [Renko Risk-Adjusted Performance] - [SPY Risk-Adjusted Performance],
        [SPY Risk-Adjusted Performance],
        0
    )
```

```
Renko Risk-Adjusted Outperformance (vs Benchmark) =
IF( HASONEVALUE( 'Specific Filtering Benchmarks'[Investment strategy] ) & HASONEVALUE( 'Specific Filtering Benchmarks'[Investment strategy] ) & SELECTEDVALUE( 'Specific Filtering Strategies'[Investment strategy] ) = SELECTEDVALUE( 'Specific Filtering Benchmarks'[Investment strategy] ),
    DIVIDE(
        [Renko Risk-Adjusted Performance] - [Benchmark Risk-Adjusted Performance],
        [Benchmark Risk-Adjusted Performance],
        0
    ),
    0
)
```

```
Long/Short Renko Performance Differential =
DIVIDE(
    CALCULATE( [Renko Risk-Adjusted Performance], 'Tactical Renko Strategies'[Investment bias] = "LONG" )
     - CALCULATE( [Renko Risk-Adjusted Performance], 'Tactical Renko Strategies'[Investment bias] = "SHORT" ),
    ABS( CALCULATE( [Renko Risk-Adjusted Performance], 'Tactical Renko Strategies'[Investment bias] = "SHORT" ) ),
    0
)
```

4. RESULTS

4.1. Performance of Long/Short Renko Patterns

4.1.1. An Overview of the Data

The most prevalent strategies are “R04_new_black”, “R01_white_trend”, “R03_new_white”, and "R02_black_trend”. However, the less frequently appearing strategies, such as “R06_double_top”, “R05_double_bottom”, “R20_bull_trap”, and “R19_bear_trap” strategies, have maintained a steady presence over the years, suggesting their potential utility in spotting trend reversals. In contrast, the least observed strategies correlate with complex patterns, such as “R18_long_tail_up_reversal”, “R17_long_tail_down_reversal”, “R13_bullish_catapult”, “R08_triple_top”, and “R07_triple_bottom”. As these patterns require significant market shifts, their infrequent occurrence is understandable.

Figure 8. Renko trades count over time

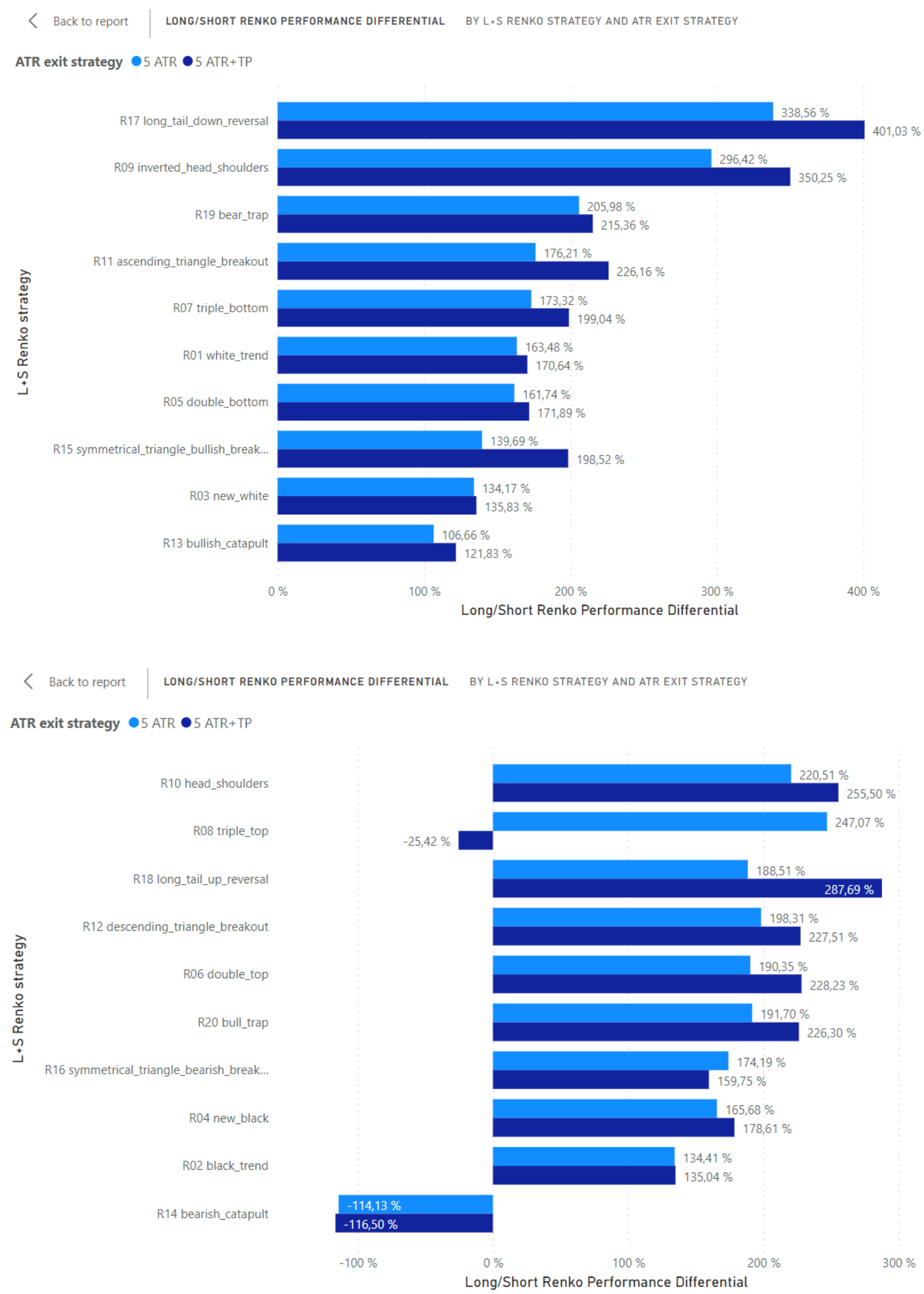
Back to report | NUMBER OF TRADES BY RENKO STRATEGY AND 5-YEAR PERIOD

L+S Renko strategy	2000	2005	2010	2015	2020	Total
R04 new_black	5 756	8 741	13 446	14 290	8 798	**51 031**
R01 white_trend	5 563	8 079	13 021	13 954	8 971	**49 588**
R03 new_white	3 259	6 244	7 583	10 594	7 117	**34 797**
R02 black_trend	2 520	5 293	6 042	8 922	6 307	**29 084**
R06 double_top	306	568	878	1 172	779	**3 703**
R20 bull_trap	263	523	897	1 098	718	**3 499**
R11 ascending_triangle_breakout	239	373	741	865	573	**2 791**
R15 symmetrical_triangle_bullish_breakout	230	362	723	863	560	**2 738**
R05 double_bottom	179	418	477	858	539	**2 471**
R19 bear_trap	106	396	434	653	471	**2 060**
R16 symmetrical_triangle_bearish_breakout	147	281	404	523	336	**1 691**
R12 descending_triangle_breakout	95	253	287	410	297	**1 342**
R18 long_tail_up_reversal	33	42	81	128	63	**347**
R17 long_tail_down_reversal	7	6	18	40	41	**112**
R13 bullish_catapult	10	17	22	36	18	**103**
R08 triple_top	9	22	8	28	26	**93**
R07 triple_bottom	2	13	22	27	19	**83**
R10 head_shoulders	7	20	25	15	7	**74**
R09 inverted_head_shoulders	4	6	12	23	14	**59**
R14 bearish_catapult	3	12	5	15	8	**43**
Total	**18 738**	**31 669**	**45 126**	**54 514**	**35 662**	**185 709**

The bar charts display performance differentials of various Renko strategies using two distinct Average True Range (ATR) exit strategies: "5_ATR+TP" (Take Profit) and "5_ATR". A higher differential suggests superior performance for long positions. The Average Long/Short Renko Performance Differential consistently indicates superior results for "5_ATR+TP", implying that setting a profit target typically yields better results than relying solely on a trailing stop. Over the last 23 years, Bullish Renko patterns have consistently outperformed bearish ones, mirroring the long-term bullish trend of the market.

Figure 9. Renko trade proportions

Figure 10. Long/short Renko performance differential



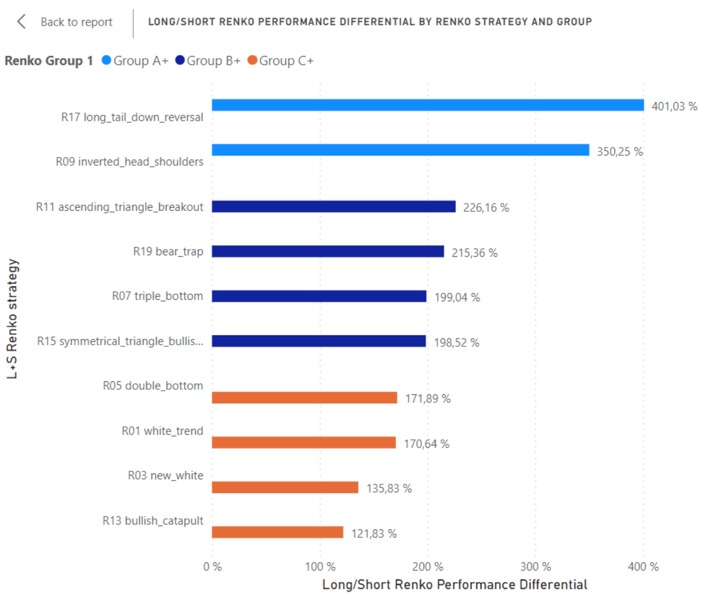
4.1.2. Classifying the Renko Patterns

We propose classifying Renko strategies into groups based on the differential between their long and short performances.

For Bullish Renko Patterns:

- Group A+: Top performers include "R17_long_tail_down_reversal" and "R09_inverted_head_shoulders", displaying differentials exceeding 350%.
- Group B+: Mid performers include "R11_ascending_triangle_breakout", "R19_bear_trap", "R07_triple_bottom", and "R15_symmetrical_triangle_bullish_breakout".
- Group C+: Lower performers, still respectable, include "R05_double_bottom", "R01_white_trend", "R03_new_white", and "R13_bullish_catapult".

Figure 11. Classifying Bullish Renko patterns

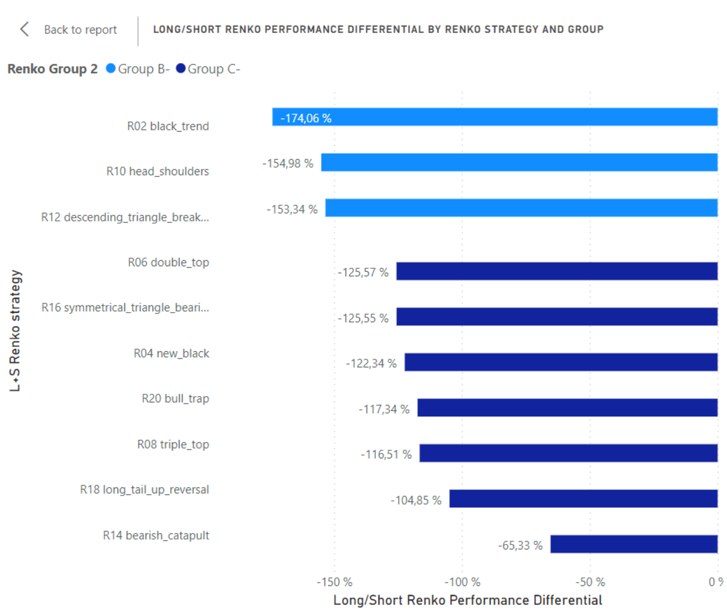


Over the past 23 years, bearish patterns have shown inconsistent performance, indicating that going against the prevailing bullish market trend often leads to underperformance. Therefore, recognizing more favorable market conditions before selecting Renko patterns is key.

For Bearish Renko Patterns under the "V4_backwardation" context:

- Group B-: Decent performers include "R02_black_trend", "R10_head_shoulders", and "R12_descending_triangle_breakout".
- Group C-: Underperformers, with inconsistent results, include "R06_double_top", "R16_symmetrical_triangle_bearish_breakout", "R04_new_black", "R20_bull_trap", "R08_triple_top", "R18_long_tail_up_reversal" and "R14_bearish_catapult".

Figure 12. Classifying Bearish Renko patterns



These findings emphasize the critical need to consider the specific market context when applying and systematically evaluating Renko strategies for the best possible outcomes.

4.2. Optimizing Renko Performance across Volatility Contexts: Top Market Segments

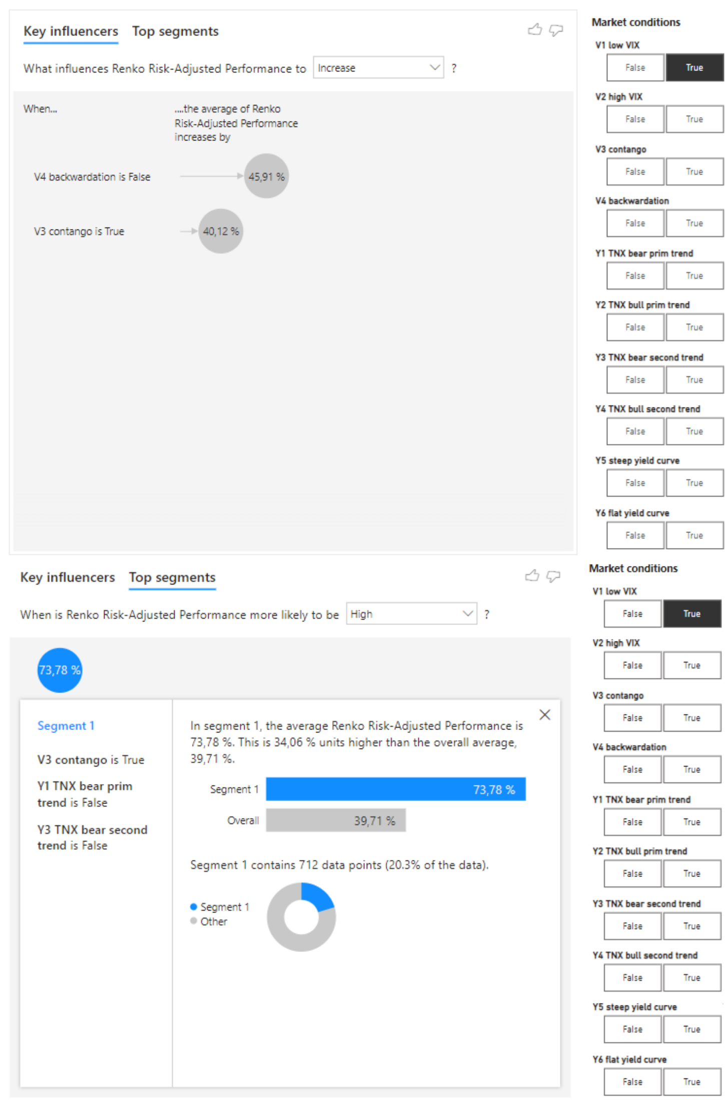
We propose using a machine learning tool, the Power BI Key Influencers visualization, to conduct a volatility-segmented analysis. Our aim is to identify and rank influential market conditions for optimizing the Renko Risk-Adjusted Performance measure of long positions across various volatility contexts.

This study considers six volatility contextual slicers:

- A: V1_low_VIX=True
- B: V1_low_VIX=False AND V2_high_VIX=False
- C: V2_high_VIX=True
- D: V3_contango=True
- E: V3_contango=False AND V4_backwardation=False
- F: V4_backwardation=True

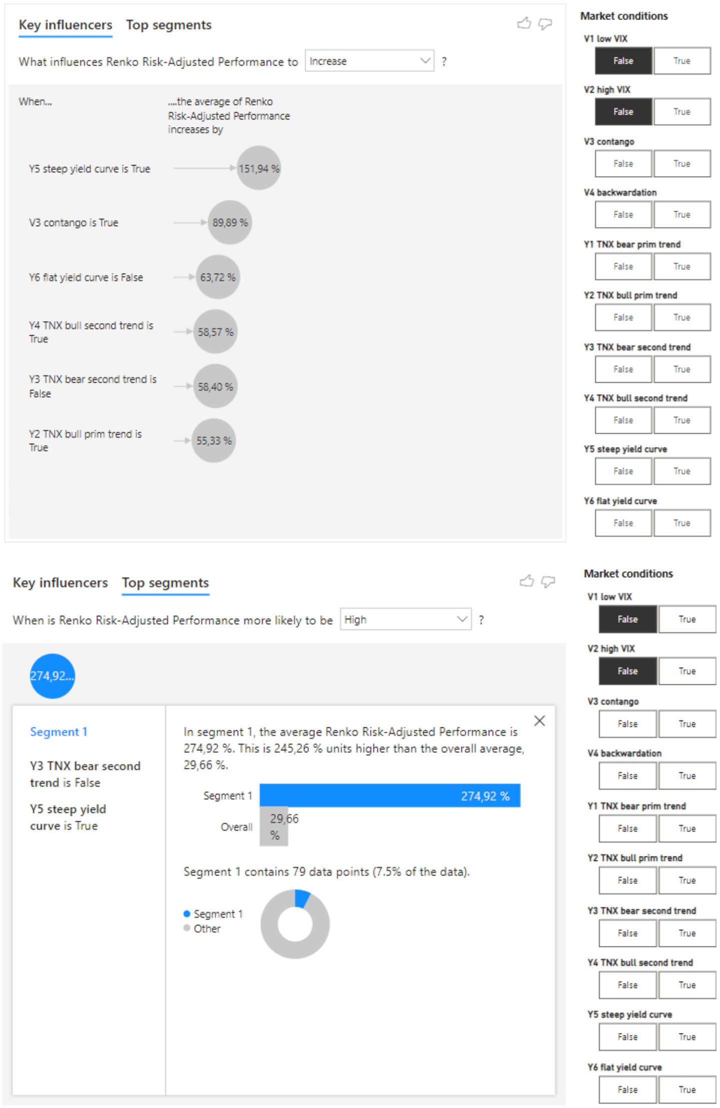
4.2.1. Context A: V1_low_VIX=True

Figure 13. Market influencers and top segment in volatility segment A



4.2.2. Context B: V1_low_VIX=False AND V2_high_VIX=False

Figure 14. Market influencers and top segment in volatility segment B

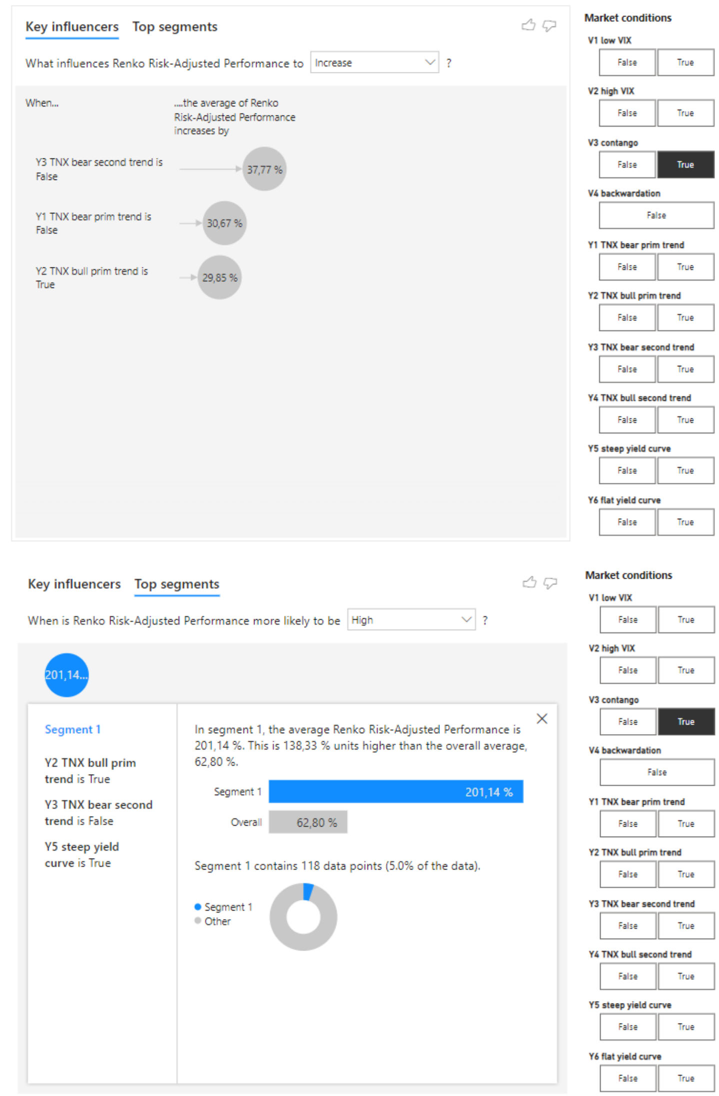


4.2.3. Context C: V2_high VIX=True

No influencer found.

4.2.4. Context D: V3_contango=True

Figure 15. Market influencers and top segment in volatility segment D



4.2.5. Context E: V3_contango=False AND V4_backwardation=False

No influencer found.

4.2.6. Context F: V4_backwardation=True

No influencer found.

4.3. Identifying Optimal Investment Strategies across Volatility Contexts: Top Strategic Clusters

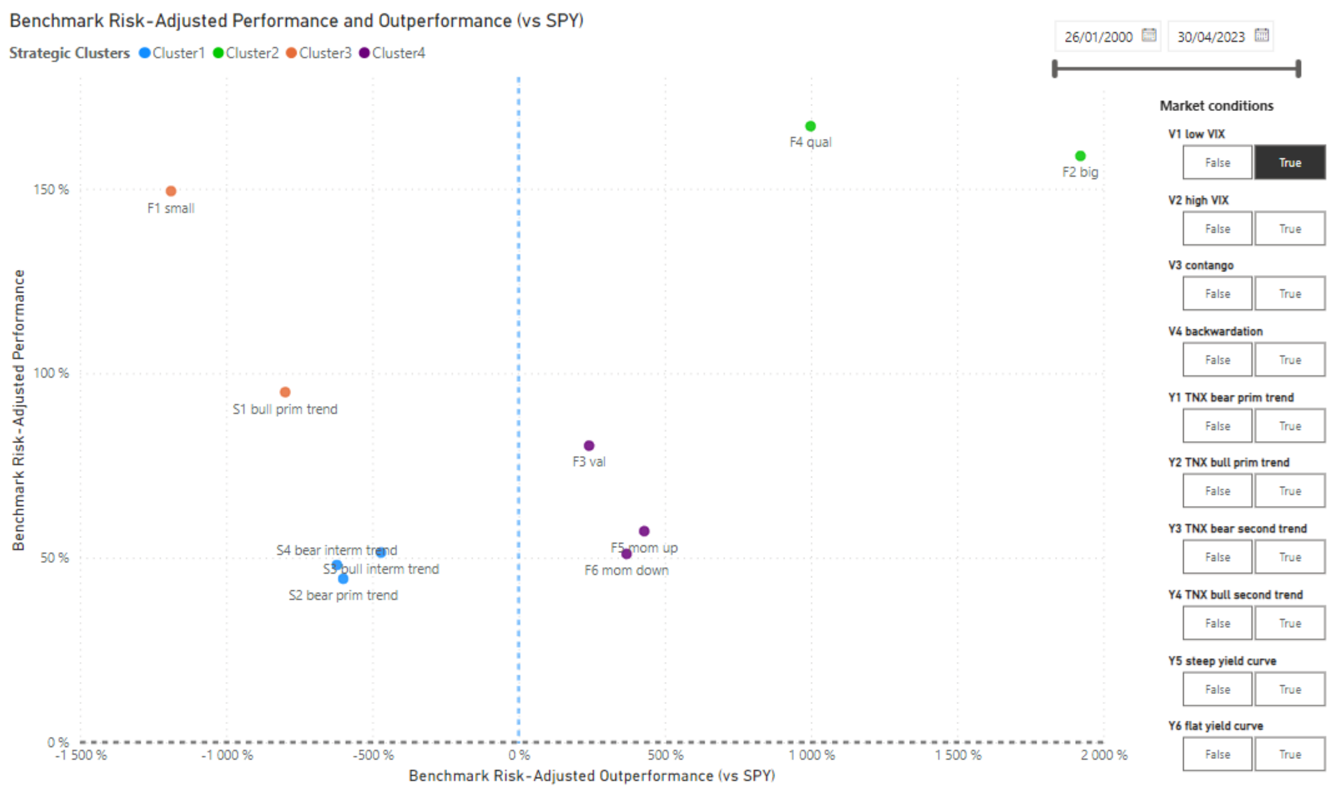
Our analysis conducts a risk-adjusted evaluation of various investment strategies, incorporating both investment factors and market trend strategies. The insights gained are:

- Risk-Adjusted Performance:
  This measure calculates the downside risk associated with the returns yielded by each strategy.
- Risk-Adjusted Performance vs SPY:
  This metric evaluates each risk-adjusted strategy against a risk-adjusted long position in the SPY ETF.
- Strategic Clusters:
  This methodology groups similar strategies, enabling a more nuanced exploration of the relationships among diverse strategies.

These insights equip investors with essential data to choose strategies aligning with their risk tolerance and return expectations. By assessing these factors, investors can craft tailored portfolios targeting their financial objectives while balancing potential risks and rewards.

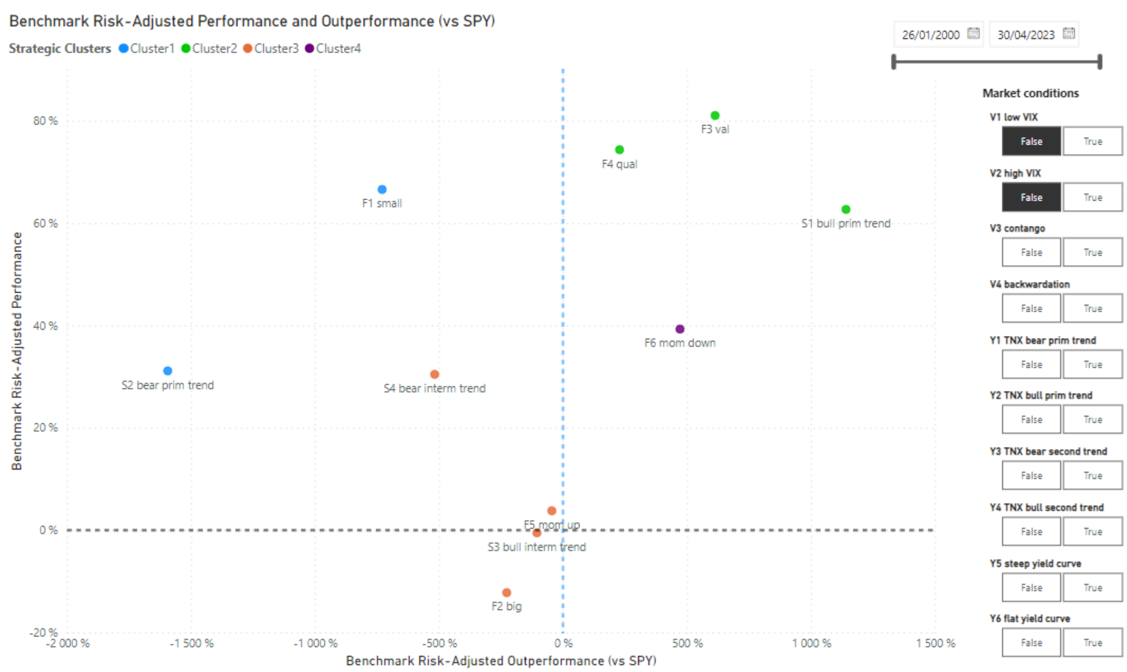
4.3.1. Context A: V1_low_VIX=True

Figure 16. Investment strategies in volatility segment A



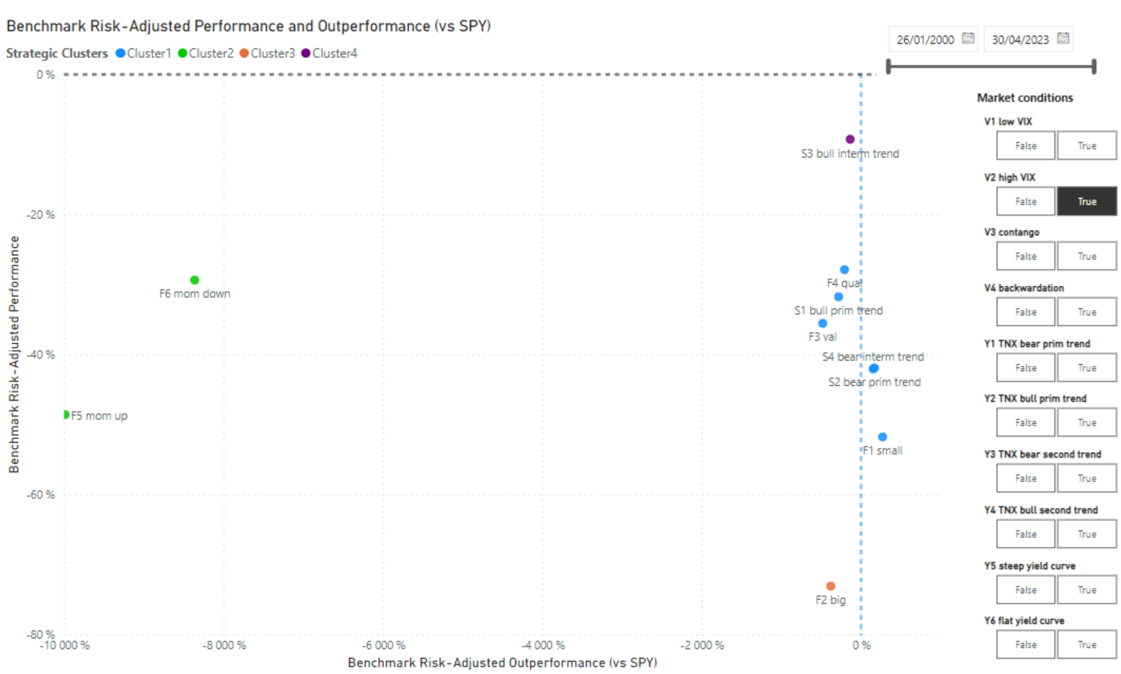
4.3.2. Context B: V1_low_VIX=False AND V2_high_VIX=False

Figure 17. Investment strategies in volatility segment B



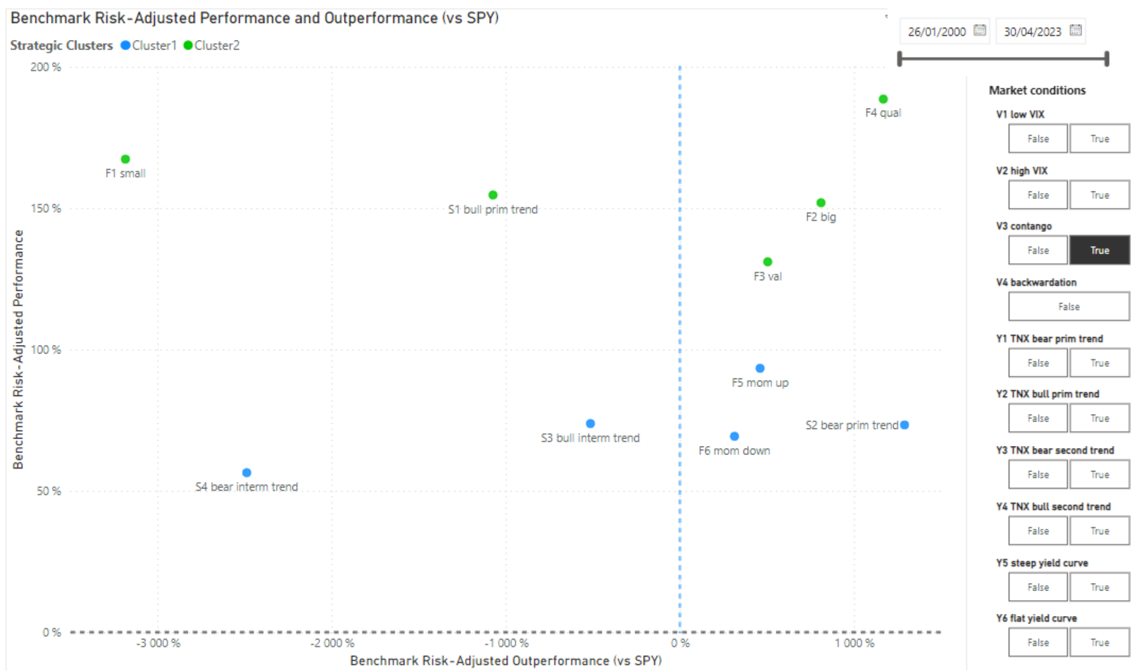
4.3.3. Context C: V2_high_VIX=True

Figure 18. Investment strategies in volatility segment C



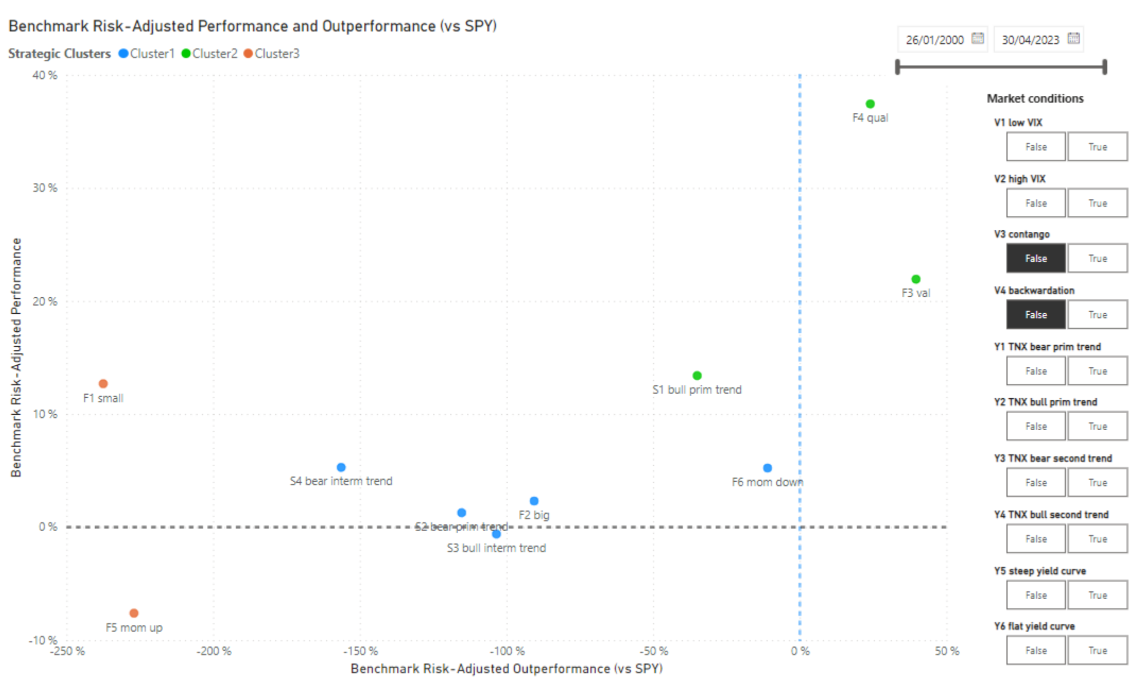
4.3.4. Context D: V3_contango=True

Figure 19. Investment strategies in volatility segment D



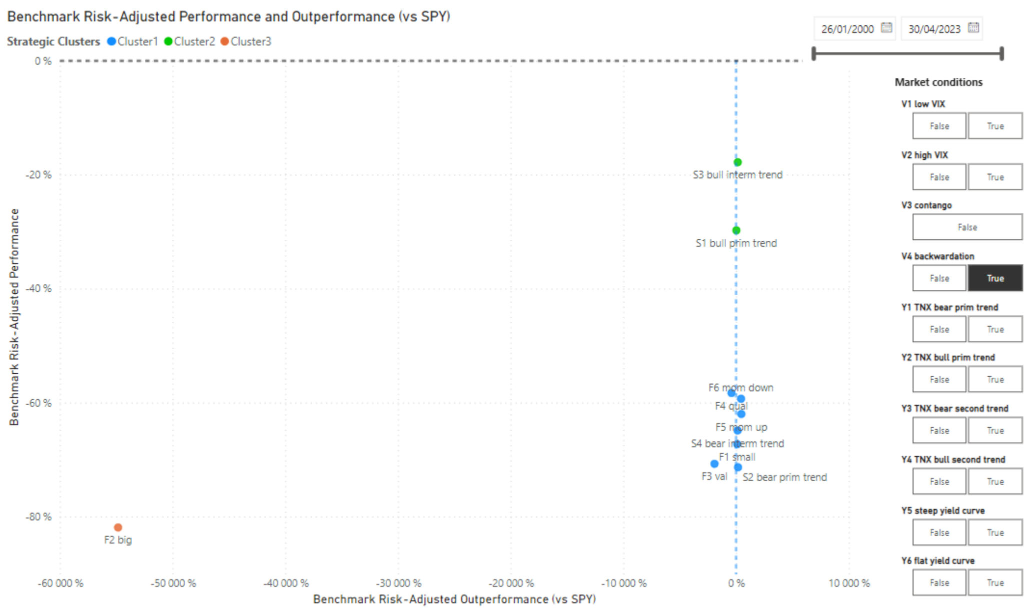
4.3.5. Context E: V3_contango=False AND V4_backwardation=False

Figure 20. Investment strategies in volatility segment E



4.3.6. Context F: V4_backwardation=True

Figure 21. Investment strategies in volatility segment F



5. DISCUSSION

5.1. Proposing a Multi-Dimensional Methodology

From analyzing Renko patterns, market conditions and investment factors across various volatility contexts, we propose a practical trading methodology. While not fully data-driven, this roadmap integrates insights from our previous study and can be combined with existing fundamental stock ranking processes.

The proposed approach segments volatility into several contexts (A...F) and examines three strategic aspects within each context: top market segment, top strategic cluster for investment factor strategies and top strategic cluster for sector trend strategies.

5.1.1. Summary of Key Insights from the Empirical Study

Figure 22. Key insights: three strategic pillars per volatility segment

VOLATILITY SEGMENTATION	TOP MARKET SEGMENT (MARKET CONDITIONS STRATEGIES)	TOP STRATEGIC CLUSTER (INVESTMENT FACTOR STRATEGIES)	TOP STRATEGIC CLUSTER (SECTOR TREND & RELATIVE STRENGTH STRATEGIES)
SEGMENT A: V1_LOW_VIX	M1 = {V3_contango, NOT Y1_TNX bear prim trend, NOT Y3_TNX bear second trend}	F4_qual OR F2_big	
SEGMENT B: NOT[V1_LOW_VIX] NOT[V2_HIGH_VIX]	M2= {NOT Y3_TNX bear second trend, Y5_steep yield curve}	F3_val OR F4_qual	S1_bull prim trend
SEGMENT C: V2_HIGH_VIX			
SEGMENT D: V3_CONTANGO	M3= {Y2_TNX bull prim trend, NOT Y3_TNX bear second trend, Y5_steep yield curve}	F4_qual OR F2_big OR F3_val OR F1_small	S1_bull prim trend
SEGMENT E: NOT[V3_CONTANGO_] NOT[V4_BACKWARDATION]		F4_qual OR F3_val	S1_bull_prim_trend
SEGMENT F: V4_BACKWARDATION			S3_bull_interm_trend OR S1_bull_prim_trend

Note: NOT[V2_CONTANGO] signifies that V2_CONTANGO=False.

Figure 23. Key insights: Renko patterns classification

BULLISH RENKO PATTERNS	BEARISH RENKO PATTERNS
GROUP A+: • "R17_long_tail_down_reversal" • "R09_inverted_head_shoulders"	
GROUP B+: • "R11_ascending_triangle_breakout" • "R19_bear_trap" • "R07_triple_bottom" • "R15_symmetrical_triangle_bullish_breakout"	**GROUP B-:** • "R02_black_trend", • "R10_head_shoulders" • "R12_descending_triangle_breakout"
GROUP C+: • "R05_double_bottom" • "R01_white_trend" • "R03_new_white" • "R13_bullish_catapult"	**GROUP C-:** • "R06_double_top" (R06) • "R16_symmetrical_triangle_bearish_breakout" • "R04_new_black" • "R20_bull_trap" • "R08_triple_top" • "R18_long_tail_up_reversal" • "R14_bearish_catapult"

5.1.2. Bullish Positioning Rules

For each volatility context and for a specific stock, we suggest the following rules:

- If two strategic aspects are validated, search for Bullish Renko patterns in A+, B+, and C+ groups. We recommend increasing trade exposure by 30%.
- (For instance, the current volatility context is "SEGMENT D: V3_contango" and, for a stock named ABC, two strategic aspects are validated: "F4_qual" and "S1_bull prim_trend").
- If only one strategic aspect is validated, search for Bullish Renko patterns in A+ and B+ groups, maintaining regular trade exposure.
- If no strategic aspect is validated, search for Bullish Renko patterns in the A+ group, reducing trade exposure by 30%.
- When structuring trades, consider either direct stock investments or 1 standard deviation Out-The-Money (OTM) debit spreads with a duration of 60 to 120 days to capitalize on the payoff ratio's convexity.

5.1.3. Bearish Positioning Rules

For each volatility context and for a specific stock, we suggest the following rules:

- In the C/V2 high VIX context, it may be preferable to adopt delta-neutral strategies that involve selling option premiums against stocks with a high implied volatility percentile, rather than pursuing directional strategies.
- In the F/ V4 backwardation context, if no strategic aspect is validated, search for Bearish Renko patterns in B- and C- groups, maintaining regular trade exposure.
- In all other contexts, if no strategic aspect is validated, search for Bearish Renko patterns in the B- group, reducing trade exposure by 30%.
- When structuring trades, consider Bearish At-The-Money (ATM) credit spreads with a duration of 30 to 60 days to capitalize on time decay, given that bearish technical patterns have historically shown lower reliability.

5.1.4. Exit Strategy

We recommend the following exit guidelines:

- Set a trailing stop and a take-profit level, each at a distance equivalent to five times the Average True Range (ATR).
- Alternatively, consider a more dynamic exit strategy. Initiate an exit when a confirmed color change in the Renko box is detected, such as when a second black box appears during a bullish sequence of white boxes. Maintain a 5-ATR-trailing stop for risk management.

In summary, our approach combines Renko chart patterns, market volatility forecasts, and detailed historical data to offer a robust, multi-dimensional, and systematic framework for decision-making in trading operations.

5.2. Introducing the Renko Directional Z-score for Quantitative Stock Selection

5.2.1. Defining the Renko Directional Z-score (RDZ)

We introduce a new indicator, the Renko Directional Z-score (RDZ), to add a fresh perspective to the visual analysis typically associated with Renko charts. This tool quantifies the strength and significance of a trend by comparing the current momentum to historical trend using Z-score. For the Bullish RDZ, it measures upward trend strength, whereas for the Bearish RDZ, it evaluates downward trend strength. This statistical computation effectively highlights overbought/oversold conditions and points out potential momentum shifts.

The RDZ, for both bullish and bearish situations, is calculated as follows:

$$RDZ = \frac{\text{ConsecutiveRenkoBars} - \mu}{\sigma}$$

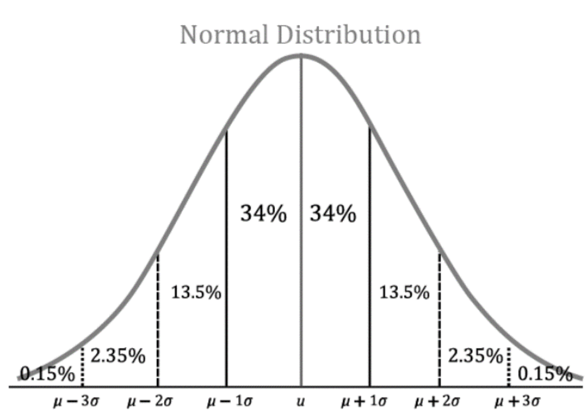
Where:

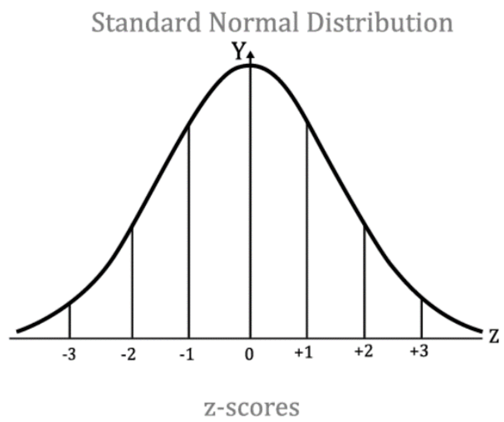
ConsecutiveRenkoBars counts the sequence of bullish or bearish Renko bars for the Bullish or Bearish RDZ respectively.

μ stands for the average number of consecutive Renko bars.

β σ is the standard deviation of consecutive Renko bars.

Figure 24. Normal distribution and Z-scores





5.2.2. Analyzing the RDZ's Technical Signals

Several traditional technical signals can be extracted and analyzed for enhanced market insights:

- Bullish RDZ Reversal Signal:
  This indicates potential uptrends when the Bullish RDZ shifts from negative to positive.
- Bullish RDZ Momentum Signal:
  This indicates bullish momentum when the Bullish RDZ is positive and increasing.
- Overbought Bullish RDZ:
  This suggests overbought stocks when the Bullish RDZ significantly exceeds its mean by more than two standard deviations (i.e., when Bullish RDZ > 2)
- Bearish Divergence on Bullish RDZ:
  This suggests potential bearish reversals when stock prices peak but the Bullish RDZ does not.

Naturally, comparable signals can be extracted from the Bearish RDZ for a comprehensive analysis.

5.2.3. Integrating the RDZ into Existing Stock-Picking Processes

Consider the RDZ as another tool in your toolbox, one that can be seamlessly integrated into existing quantitative stock-picking processes:

- Fundamental Analysis Integration:
  The RDZ's signals can enhance fundamental analysis. For instance, preference could be given to undervalued stocks showing Bullish RDZ reversal signals.
- Quantitative Factor Models:
  The RDZ could serve as an additional factor. For instance, stocks showing a high Bullish RDZ might receive higher momentum scores.
- Portfolio Construction:
  Stocks displaying strong Bullish RDZ may receive larger allocations, while those with robust Bearish RDZ could be underweighted.
- Risk Management:
  The RDZ can offer an additional layer of risk management. Overbought Bullish RDZ signals might necessitate position size reduction or risk hedging.
- Entry and Exit Timing:
  The RDZ primarily functions as a timing tool. Bullish RDZ reversal signals might trigger entry, while Overbought Bullish RDZ or Bearish divergences on Bullish RDZ could indicate exit points.
- Multi-Asset Portfolio:
  The RDZ can be useful in a multi-asset context with preference possibly given to asset classes showing Bullish RDZ within an asset allocation strategy.
- Machine Learning Models:
  The RDZ, as a statistical indicator, could contribute to enhance the predictive accuracy of machine learning models used for stock selection or ETF allocation.

5.3. Introducing the Leading RDZ: a VIX-Adjusted Market Sentiment Indicator

5.3.1. Defining the Leading RDZ

With the Leading RDZ, we push Renko analysis up to a new level by engineering a sophisticated and innovative market breadth indicator. It measures the proportion of S&P 500 stocks displaying overbought Bullish and oversold Bearish RDZ conditions, providing a means to detect market extremes, confirm prevailing trends and detect divergences signaling potential market shifts.

The true originality lies in the uniqueness of these thresholds of overextension, which are adjusted according to the VIX term structure, represented by the ratio EMA(VIX3M,5) / EMA(VIX,5). By embedding future volatility forecasts, we have forged a tool that is more dynamic, echoing the inherent fluctuation present in market conditions.

Furthermore, we introduce a scaling factor "k" that adjusts in response to the VIX Z-score. This scaling allows the thresholds for overbought and oversold conditions to marginally increase with higher VIX levels and decrease with lower VIX levels, offering even more granular control and insight into market behavior.

- Overextended Bullish Component Formula (OBUC):

$$\text{OBUC} = \frac{\textit{Number of stocks with } \left(\textit{Bullish RDZ} > 2k\,\frac{EMA(\,VIX3M, 5\,)}{EMA(\,VIX, 5\,)}\right)}{\textit{Total number of S\&P 500 stocks}}$$

Here, "k" is a scaling factor, centered around 1 and responsive to future volatility

$$k = 1 + \frac{\text{VIX Zscore}}{20} = 1 + \frac{\text{VIX} - \mu}{20\sigma}$$

Where μ is the VIX population mean and β the standard deviation.

- Overextended Bearish Component Formula (OBEC):

$$\text{OBEC} = \frac{Number\ of\ stocks\ with\ \left(Bearish\ RDZ > 2k\,\frac{EMA(\,VIX, 5\,)}{EMA(\,VIX3M, 5\,)}\right)}{Total\ number\ of\ S\&P\ 500\ stocks}$$

Here, “k” is the same scaling factor, adjusted with the VIX Z-score.

5.3.2. Visualizing and Interpreting the Leading RDZ

The OBUC and OBEC are plotted on a scatter plot, offering a visual interpretation of market breadth. Each quadrant on the scatter plot conveys a unique market sentiment:

- Quadrant I (High OBUC, Low OBEC):
  This indicates a strong bullish sentiment with most stocks in overbought conditions, suggesting potential upward market trend.
- Quadrant II (High OBUC, High OBEC):
  This represents a volatile or uncertain market, with many stocks either overbought or oversold, suggesting disparity across sectors or investment styles, necessitating drill down investigation via sector-specific or group-specific Leading RDZ calculations.
- Quadrant III (Low OBUC, High OBEC):
  This indicates a strong bearish sentiment with most stocks in oversold conditions, suggesting possible downward market trend.
- Quadrant IV (Low OBUC, Low OBEC):
  This represents a calm or stagnant market, with few stocks either overbought or oversold, suggesting less directional opportunities and relative market stability.

This scatter plot analysis can be applied not just to the S&P 500, but also to each sector within the index, and even to various investment style groups of stocks, thereby offering a granular view of market sentiment.

In summary, the Leading RDZ, a pioneering market breadth indicator, harnesses the principles of Renko charts to examine overbought and oversold conditions in the S&P 500 or specific stock clusters. Seamlessly integrating future volatility expectations, this tool provides a compass for market analysts and traders. It empowers them to differentiate between various market sentiments - bullish, bearish, volatile, or calm - and interpret the significance of their transitions.

5.4. Limitations of the Study and Future Research Directions

5.4.1. Limitations

Like any empirical research, this study has inherent limitations, primarily its reliance on historical data for backtesting. While past performance can offer valuable insights, it doesn't guarantee future results. Therefore, any interpretations drawn from past data should be approached with caution and regularly reassessed against up-to-date market data to stay in sync with market dynamics.

Moreover, external variables such as geopolitical shifts, policy changes, or Black Swan events represent a factual limitation. These factors lie beyond the predictive capacity of any systematic analytical model. Despite providing a roadmap based on Renko patterns, volatility contexts, and fundamental ratios, this methodology is not immune to these unpredictable factors.

5.4.2. Future Research Directions

This study exclusively targets the U.S. equity market, possibly limiting its applicability. Yet, it paves the way for evaluating our methodology's adaptability across varied markets. Training neural networks on historical data could reveal even richer nuances with Renko chart patterns.

Additionally, leveraging AI in detailed market simulations could precisely uncover subtle anomalies like irregular cycles and prevalent trader biases. By combining Renko techniques with such advancements, we could gain deeper, more actionable market insights. The emergent world of decentralized finance (DeFi) and crypto sectors could provide a fertile ground for refined Renko analysis. As financial systems rapidly evolve, exploring innovative smart contract strategies, especially integrating the RDZ, could also become a captivating avenue.

In summary, the combination of cutting-edge data analytics and revolutionary AI with traditional technical analysis, could very well shape the future landscape for market technicians. This synergistic approach has the potential to increase the versatility and relevance of technical analysis in a world increasingly influenced by data and AI.

6. CONCLUSION

In this study, we embarked on an exploration of the intricate relationship between market implied volatility, investment strategies, and the less frequently examined ATR-based Renko chart patterns. Our objective was to construct a systematic, flexible, and practical trading methodology that could serve as a reliable beacon for investors and traders in navigating diverse market conditions. We categorized volatility into multiple segments, and within each, we examined three strategic pillars: market conditions, investment factors, and sector trends.

Our tactical roadmap combines the strengths of technical and fundamental analysis, while blending the clarity of Renko charts with a nuanced understanding of volatility contexts. The multidimensional and adaptive nature of this approach, with its ability to simultaneously consider a spectrum of factors and adjust to market volatility, provides traders with a comprehensive decision-making framework. As with any empirical research, our insights are drawn from historical data, requiring ongoing validation with live market data to ensure relevance and accuracy.

Leveraging the principles of Renko charts, we introduced two groundbreaking technical indicators: the Renko Directional Z-score (RDZ) and the Leading RDZ. The RDZ quantifies the strength and significance of trends displayed by Renko charts using a Z-score approach, promising to enhance various trading aspects from quantitative factor models to risk management and portfolio construction. The Leading RDZ, a dynamic market breadth indicator, monitors market extremes within S&P 500 stocks while incorporating future volatility expectations, thereby offering an original lens through which to interpret market sentiment.

Looking forward, we perceive abundant opportunities to expand this practical research. Applying our methodology to different markets and integrating it with emerging technologies like artificial intelligence and machine learning, holds substantial promise. Future research could also focus on refining the ATR and RDZ parameters to resonate with the rhythm of market cycles.

In essence, this applied research sought to recalibrate the scope of technical analysis through the creative use of Renko charts. This exciting reinterpretation of traditional techniques has the potential to uncover additional strata of market analysis, leading to more precise and insightful discoveries. We hope that this contribution will incite a paradigm shift among market technicians, paving the way for future advancements that blend traditional technical analysis seamlessly with contemporary quantitative data analytics.

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The Similarities in Various Markets and Timeframes, Through Quantitative Comparison Methods, and Its Application to Trading Systems

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ABSTRACT

While the extent of mutual resemblances in the charts of various markets and timeframes has been widely discussed by employing mathematics and physics, this thesis presents several simple ways to measure such similarities and discusses their application to trading systems. The observations were made on the past 30-year worth of data of monthly, weekly and daily on S&P500, Nasdaq Composite, Nikkei225, TOPIX, USD-JPY and on a "simulated market", generated by random numbers, in which the price fluctuations follow a normal distribution.

First, it was learned that the deviation rate from moving averages and price fluctuation range irrespectively showed long-term convergence to a constant value or a range, when taking ATR into account and processing them. This allowed to observe strong similarities and to discover outliers without adjusting parameters per market. Additionally, while the convergence was also observed in the simulated market, whose appearance resembled the actual one, the converging value apparently differed.

Second, in respect to the durability of moving averages, the relative magnitude of price movements, probability of price continuity, and the behavior of major technical indicators, it was learned that some of the values were almost identical across all markets and timeframes, including simulated markets, suggesting a strong similarity, whereas others showed regular and tendentious differences. These observations are statistically processed by distribution analysis based on standard deviation, arithmetic mean and frequency distribution.

For the purpose of applying the research results to trading systems, adopting the probability that is nearly common to each market to improve their performances and utilizing outliers against other markets are discussed. In addition, methods for adjusting the parameters of technical indicators reflecting the values that tend to vary by market are also discussed.

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INTRODUCTION

For investors who apply technical analyses to different markets and timeframes, this thesis intends to devise quantitative methods to see if the same approach works at different markets and timeframes. Different markets have different currency units and digits, and different timeframes have different magnitudes of price fluctuations. The methods ought to be simple so that investors can resolve the question of whether the methodology and parameters should be changed for each market and timeframe. Although there seems to be no settled opinion on this point, two types of ideas exist.

a. Different markets and timeframes have different characteristics, so methods and parameters should be changed accordingly.
b. If the same method does not work in different markets and timeframes, it cannot be considered a robust method.

These are two opposites. An example of the former is that many of the automated trading systems sold are market and timeframe specific.*[1] Regarding the latter, Pardo explains it in terms of "scalability" and recommends multi-market, multi-period verification using the same system (Pardo 2008, pp. 75-76, pp. 261-262).

This discussion ends in to the question of how much similarity there is among them. Some perspectives on how investors can practically measure the similarity are proposed on this thesis.

MATERIALS AND METHODS

2.1 DATA USED

Daily, weekly, and monthly data on S&P500, Nasdaq Composite, Nikkei225, TOPIX, USD-JPY, and WTI Crude Oil for the past 30 years were used. In order to validate the smaller timeframes, from 1-minute to 60-minutes timeframes of the year 2022 for the markets corresponding to the above were also used.*[2]

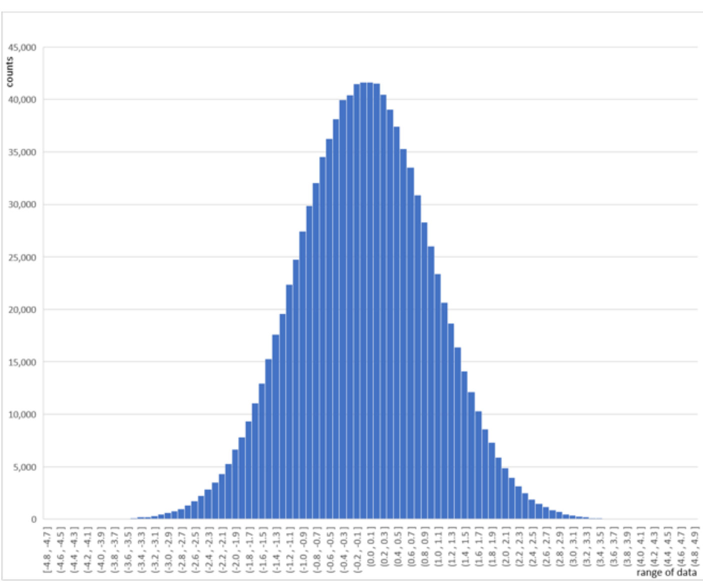
2.2 CREATION OF SIMULATED MARKET

In order to verify the similarity of markets, a simulated market was created to compare and contrast with actual markets. The simulated market is a so-called random walk market where price fluctuations follow a normal distribution. It was created based on an Excel file for generating simulated markets which had been posted on the members-only website of The Nippon Technical Analysts Association (NTAA), with modifications (Figure 1).*[3]

Figure 1 Examples of graphing the price actions with 350,000 random prices

The values corresponding to price fluctuations created by this method follow a normal distribution, as shown in Figure 2.

Figure 2 Standard normal distribution data generated by NORMINV function (2^20 cases)



2.3 USING TYPICAL PRICE IN CONJUNCTION WITH CLOSE PRICE

In this thesis, the typical price (hereinafter referred to as "TP") were used in addition to the close price (hereinafter referred to as "Close"), as the use of TP often stabilized a technical indicator or highlighted the original purpose of the indicator.[*4]

2.4 APPLICATIONS AND PROGRAMMING LANGUAGES USED

Microsoft Excel was used. Various functions and VBA programming were used for data aggregation and verification.

2.5 TECHNICAL INDICATORS AND ANALYSIS METHODS

In each of the following analyses, the simulated market and the actual market were analyzed using the same method. Also, the differences between the two, as well as the differences between the markets, were analyzed.

2.5.1 Generalized Volatility Ratio (GVR) (invented by the author)

GVR is the absolute value of {(TP of the bar - TP of the previous bar)/ATR(14)}. Using ATR as a divisor, it aims to obtain a generalized value that allows direct numerical comparison between markets in terms of the magnitude of price fluctuations. The unit is %.

2.5.2 Generalized Deviation ratio from Moving Average(GDMA) (invented by the author)

The absolute value of {(TP - EMA(20))/ATR(14)}, where ATR is used as a divisor for the same purpose as GVR.

*2.5.3 Durability of Moving Averages (DoMA) (named by the author)[*5]*

Number of times the MA turned / total number of bars in the measurement period. Moving averages are calculated using TP with EMA (5, 20, 50).

2.5.4 Analyzing the Distribution of Representative Technical Indicators and Price Fluctuations Based on Their Standard Deviations

The distribution based on the standard deviation at TP and Close(Bollinger bands), and that of RSI values were compared to the normal distribution. The calculation periods used were the common 25 and 14. The distribution of price fluctuations, which was said to be close to the normal distribution, was also verified.

2.5.5 Analysis of the Number of Consecutive Rises And Falls

The percentage of occurrences for each number of consecutive rises and falls were measured[*6]. It was also analyzed whether the data had any meanings or not.

RESULTS

3.1 GVR

In the simulated market*[7], GVR converged to 50% (units abbreviated below) as measured at TP. However, when the number of data was as small as monthly or weekly, there was a variation of less than 3 around 50. The data ranged from 0 to 300, with almost 90% of the data within 100, and the values measured at TP were generally about 13 lower than those measured at Close (Table 1).

Table 1 GVR measured in the simulated market

Number of data	Simulation		
	GVR (TP)	Percentage of within 100	GVR (Close)
360	52.7%	83.6%	66.5%
1,565	47.9%	90.9%	60.0%
7,500	50.2%	89.4%	62.2%
6,000	50.3%	89.3%	62.6%
24,000	50.6%	89.2%	63.0%
70,000	50.4%	89.3%	62.8%
350,000	50.3%	89.3%	62.6%

In the actual market, stock indices were slightly larger in GVR than FX and commodity markets, with the former averaging in the upper 40s and the latter in the lower 40s in daily or above timeframes*[8]. In less than 60-minutes timeframes, there were little difference between markets, with values in the lower 40s. The values of 1-minute timeframe were slightly larger than those of the other minute timeframes. In any case, the values were smaller than the simulated market with a central value of 50. About 95% of the values were within 100, a higher percentage than in the simulated market (Table 2). Although there were very rare instances of values above 200, the values were almost always between 0 and 200.

Table 2 GVR measured in the actual markets at TP

	S&P500		NASDAQ		Nikkei225		TOPIX	
	GVR	Percentage of within 100	GVR	Percentage of within 100	GVR	Percentage of within 100	GVR	Percentage of within 100
Monthly	42.6%	95.1%	45.8%	93.3%	47.5%	89.0%	42.0%	93.6%
Weekly	42.4%	94.6%	44.6%	94.0%	46.1%	91.8%	46.9%	91.2%
Daily	47.1%	91.0%	50.7%	88.8%	53.4%	85.6%	55.4%	85.7%
60 mins	42.2%	91.0%	42.4%	90.5%	41.5%	92.7%	–	–
15 mins	41.4%	92.9%	41.4%	94.1%	41.9%	92.6%	–	–
5 mins	41.2%	93.8%	40.7%	94.0%	42.2%	93.2%	–	–
1 min	43.5%	92.8%	42.1%	93.3%	44.7%	92.0%	–	–

Table 2 GVR measured in the actual markets at TP (continued)

	USDJPY		Crude Oil		Gold	
	GVR	Percentage of within 100	GVR	Percentage of within 100	GVR	Percentage of within 100
monthly	40.6%	93.6%	42.4%	96.0%	44.2%	91.1%
weekly	38.9%	95.1%	40.9%	95.4%	46.6%	90.5%
daily	38.0%	95.3%	41.3%	94.2%	39.2%	94.9%
60 mins	39.2%	93.7%	41.2%	91.3%	39.3%	92.7%
15 mins	40.4%	93.3%	40.8%	92.9%	39.9%	93.8%
5 mins	41.4%	93.6%	41.0%	93.6%	40.6%	94.1%
1 min	44.9%	91.7%	44.3%	91.8%	44.1%	92.3%

3.2 GDMA

In the simulated market measured at TP, GDMA converged to 130, with 94% within 300 (Table 3). GDMA at Close were almost the same, but they were slightly larger and the percentage that settles within 300% was smaller.

Table 3 GDMA measured in the simulated market

Number of Data	Simulation			
	GDMA (TP)	Percentage of within 300	GDMA (Close)	Percentage of within 300
360	129.6%	93.0%	131.3%	91.9%
1,565	116.0%	95.0%	118.2%	94.7%
7,500	127.2%	93.9%	129.5%	93.7%
6,000	130.9%	93.1%	133.0%	92.9%
24,000	128.0%	94.2%	130.3%	93.9%
70,000	130.3%	93.9%	132.5%	93.5%
350,000	130.8%	93.7%	133.1%	93.2%

In the actual market, stock indices were larger in value than FX and commodity markets, with the former averaging in the mid-130s and the latter just under 110 in daily or above timeframes. The differences between the markets were small in the minute-timeframes, but slightly larger in the stock indices, and also larger in the 60-minutes timeframes than in the 15- minutes or under. The probability of getting within 300 was clearly higher than in the simulated market, averaging 96.2% (Table 4).

Table 4 GDMA measured in the actual markets at TP

	S&P500		NASDAQ		Nikkei225		TOPIX	
	GDMA	Percentage of within 300	GDMA	Percentage of within 300	GDMA	Percentage of within 300	GDMA	Percentage of within 300
monthly	154.9%	91.8%	155.0%	93.8%	130.1%	94.1%	122.9%	96.5%
weekly	126.3%	96.6%	134.1%	95.7%	122.3%	95.1%	126.8%	94.4%
dairy	125.7%	96.7%	139.0%	94.0%	132.1%	93.7%	138.5%	92.4%
60mins	126.1%	93.8%	129.5%	93.4%	114.9%	95.6%	–	–
15mins	114.8%	96.1%	115.3%	96.0%	115.1%	96.3%	–	–
5mins	111.1%	96.7%	109.9%	96.7%	113.5%	96.4%	–	–
1mins	114.6%	96.4%	111.5%	96.8%	119.2%	95.4%	–	–

Table 4 GDMA measured in the actual markets at TP (continued)

	USDJPY		Crude Oil		Gold	
	GDMA	Percentage of within 300	GDMA	Percentage of within 300	GDMA	Percentage of within 300
monthly	118.8%	94.7%	97.5%	97.9%	129.3%	95.8%
weekly	105.9%	97.3%	104.0%	98.0%	110.4%	96.7%
dairy	102.4%	98.3%	109.0%	98.9%	102.9%	98.5%
60mins	112.7%	96.0%	113.4%	96.9%	108.5%	97.3%
15mins	104.2%	97.2%	109.0%	97.4%	103.9%	97.6%
5mins	103.2%	97.3%	108.0%	97.3%	102.7%	97.9%
1mins	123.6%	94.4%	114.4%	96.3%	113.8%	96.1%

3.3 DoMA

Measurements were taken at 5, 20, and 50 EMAs. When measured at TP, DoMA persisted longer than at Close in all markets and timeframes without exception. Therefore, only the values measured at TP, which were more persistent, were presented here. First, the values measured in the simulated markets are shown (Table 5).

Table 5 DoMA measured in the simulated market

	Simulation					
	DoMA(5)		DoMA(20)		DoMA(50)	
Number of Data	TP	Close	TP	Close	TP	Close
360	4.7	3.7	10.7	6.6	16.3	10.4
1,565	4.3	3.4	9.1	7.1	13.5	11.5
7,500	4.7	3.8	8.9	7.3	13.1	10.2
6,000	4.7	3.8	8.9	7.1	14.0	11.0
24,000	4.7	3.7	8.6	6.9	13.7	10.9
70,000	4.7	3.8	8.9	7.2	14.2	11.3
350,000	4.6	3.7	8.9	7.1	14.0	11.2

In the actual market (Table 6), the overall trend was as follows: 1) the 1-minute timeframes were the closest to the simulated market, and the values increased slightly as the timeframe expanded, 2) with the exception of DoMA(5), the values were larger than those of the simulated market. The DoMA(5) were almost the same as the simulated market except for the U.S. stock indices (weekly and monthly). 3) the U.S. stock indices (especially the 20 and 50 DoMA above 60 minutes) showed larger values than the other markets.

Table 6 DoMA measured in the actual markets at TP

	S&P500			NASDAQ			Nikkei225			TOPIX		
	DoMA(5)	DoMA(20)	DoMA(50)	DoMA(5)	DoMA(20)	DoMA(50)	DoMA(5)	DoMA(20)	DoMA(50)	DoMA(5)	DoMA(20)	DoMA(50)
monthly	5.9	17.0	34.0	6.3	15.5	24.3	4.9	9.7	30.9	5.6	14.8	17.9
weekly	5.3	11.5	22.4	5.2	11.5	23.8	4.6	10.7	16.4	4.8	10.5	16.1
dairy	4.8	9.5	16.3	4.8	9.6	17.2	4.4	8.5	14.6	4.4	8.6	14.9
60mins	4.8	10.8	19.9	4.7	11.2	20.1	4.8	9.0	16.3	–	–	–
15mins	4.8	9.9	16.5	4.8	9.6	16.6	4.8	9.8	15.5	–	–	–
5mins	4.7	9.4	15.3	4.8	9.4	15.5	4.8	9.5	15.6	–	–	–
1mins	4.6	9.0	13.9	4.7	9.2	14.7	4.8	9.3	15.1	–	–	–

Table 6 DoMA measured in the actual markets at TP (continued)

	USDJPY			Crude Oil			Gold		
	DoMA(5)	DoMA(20)	DoMA(50)	DoMA(5)	DoMA(20)	DoMA(50)	DoMA(5)	DoMA(20)	DoMA(50)
monthly	4.9	13.6	13.1	5.2	7.2	17.9	5.2	20.2	21.9
weekly	4.7	9.2	16.3	5.0	9.5	15.3	4.7	7.8	18.8
dairy	4.7	9.1	15.0	4.8	9.4	14.3	4.8	9.4	13.6
60mins	4.6	10.4	18.4	4.7	10.1	15.9	4.8	9.6	16.7
15mins	4.6	9.3	15.8	4.7	9.5	15.9	4.6	9.4	15.8
5mins	4.6	8.8	14.4	4.7	9.2	15.2	4.6	8.8	14.5
1mins	4.6	9.0	13.9	4.6	9.1	14.6	4.6	8.9	13.8

3.4 ANALYZING THE DISTRIBUTION OF REPRESENTATIVE TECHNICAL INDICATORS AND PRICE FLUCTUATIONS BASED ON THEIR STANDARD DEVIATIONS

3.4.1 Bollinger bands

In the simulated market, the distribution measured at TP was slightly thinner in the middle of the distribution and thicker toward the edges than at Close (Table 7). Note that this is far from a normal distribution and is unrelated to it.

Table 7 Price distribution based on Bollinger bands measured in the simulated market

Number of Data	Simulation		
	Standard deviation	TP	Close
70,000	>2σ,<−2σ	13.4%	12.5%
	1σ~2σ,−2σ~−1σ	43.9%	43.5%
	<1σ,>−1σ	42.7%	44.0%
350,000	>2σ,<−2σ	13.2%	12.5%
	1σ~2σ,−2σ~−1σ	43.9%	43.3%
	<1σ,>−1σ	42.9%	44.2%

In the actual market, there were no significant differences among markets except for some monthly exception values(Table 8)*9. In the timeframe, focusing on values above 2σ, the daily values were about the same or slightly smaller than the simulated market. The weekly values were slightly larger, and the monthly values were much larger (Nikkei225 and USD-JPY were exceptions). In the 1-minute timeframe, the values were almost the same as in the simulation, slightly larger in the 5-minutes timeframe, and maximum in the 15 or 60-minutes timeframe.

Table 8 Price distribution based on Bollinger bands measured in the actual markets at TP

	Standard deviation	S&P500	NASDAQ	Nikkei225	TOPIX	USDJPY	Crude Oil	Gold
monthly	>2σ,<-2σ	17.0%	19.3%	14.3%	14.3%	12.5%	16.1%	19.7%
	1σ~2σ,-2σ~-1σ	58.9%	54.2%	42.6%	42.3%	48.5%	38.4%	51.4%
	<1σ,>-1σ	24.1%	26.5%	43.2%	43.5%	39.0%	45.5%	29.0%
weekly	>2σ,<-2σ	13.3%	13.8%	13.3%	13.6%	15.2%	15.6%	15.1%
	1σ~2σ,-2σ~-1σ	50.2%	50.6%	45.3%	47.0%	41.2%	41.2%	37.5%
	<1σ,>-1σ	36.5%	35.6%	41.4%	39.3%	43.5%	43.2%	47.4%
dairy	>2σ,<-2σ	12.0%	12.7%	12.5%	13.1%	13.4%	12.3%	13.4%
	1σ~2σ,-2σ~-1σ	49.1%	49.2%	45.2%	43.6%	43.4%	47.0%	42.6%
	<1σ,>-1σ	38.9%	38.2%	42.4%	43.3%	43.3%	40.8%	44.1%
60 mins	>2σ,<-2σ	15.3%	15.6%	13.9%	–	15.2%	14.9%	14.4%
	1σ~2σ,-2σ~-1σ	42.1%	41.8%	42.0%	–	40.6%	41.1%	40.5%
	<1σ,>-1σ	42.6%	42.6%	44.1%	–	44.2%	44.1%	45.1%
15 mins	>2σ,<-2σ	14.9%	14.8%	14.2%	–	14.7%	14.8%	14.3%
	1σ~2σ,-2σ~-1σ	40.1%	40.0%	41.9%	–	38.6%	40.2%	40.6%
	<1σ,>-1σ	45.0%	45.3%	44.0%	–	46.6%	45.0%	45.0%
5 mins	>2σ,<-2σ	14.2%	14.3%	13.6%	–	13.6%	13.9%	13.3%
	1σ~2σ,-2σ~-1σ	41.1%	40.2%	42.2%	–	39.5%	41.1%	41.7%
	<1σ,>-1σ	44.6%	45.6%	44.2%	–	46.9%	45.0%	45.0%
1 mins	>2σ,<-2σ	13.6%	13.7%	13.6%	–	13.2%	13.4%	13.1%
	1σ~2σ,-2σ~-1σ	42.3%	41.8%	42.1%	–	41.0%	41.9%	42.3%
	<1σ,>-1σ	44.2%	44.5%	44.3%	–	45.8%	44.8%	44.5%

3.4.2 RSI

The upper and lower thresholds were set at 90/10, 80/20, and 70/30 to measure how many of the prices settled within the thresholds. In the simulated market, based on Close, slightly less than 4.6% (2σ) exceeded the 80/20 threshold; on TP, as with Bollinger bands, the outside of the distribution was thicker (Table 9).

Table 9 Price distribution based on RSI measured in the simulated market

Number of Data	Simulation		
		TP	Close
70,000	90/10	1.8%	0.6%
	80/20	7.0%	3.7%
	70/30	17.0%	12.0%
350,000	90/10	1.6%	0.5%
	80/20	7.2%	3.7%
	70/30	17.6%	12.3%

Both TP and Close measurements are included here (Table 10) in order to use them for the parameter adjustment described later in 4.5.3 and because the differences in values are somewhat large. In the actual market, there were few differences among markets, except that the tips of the distribution were noticeably thicker at weekly and monthly timeframes of the U.S. stock indices. In the timeframes, the daily and the above timeframes of the U.S. stock indices were also striking. Looking around the whole markets, the values in the 80/20 were much higher than the 7.2% and 3.7% of the simulated market for the 60-minute and above timeframes across all markets. The smaller timeframes were not much different from the simulated market, and the 1-minute timeframe was almost identical to the simulated market. The trend of "larger values for larger timeframes" was also similar to that of the Bollinger bands.

Table 10 Price distribution based on RSI measured in the actual markets

		S&P500		NASDAQ		Nikkei225		TOPIX		USDJPY		Crude Oil		Gold	
		TP	Close	TP	Close	TP	Close	TP	Close	TP	Close	TP	Close	TP	Close
monthly	90/10	9.1%	3.3%	8.8%	3.9%	3.3%	2.7%	5.1%	3.6%	5.7%	0.9%	3.0%	0.0%	2.4%	0.0%
	80/20	27.5%	15.7%	24.5%	18.7%	10.0%	9.4%	12.4%	11.2%	15.1%	9.4%	10.3%	3.3%	16.1%	5.5%
	70/30	48.3%	39.0%	43.2%	32.3%	24.2%	22.4%	25.1%	23.6%	25.7%	21.1%	25.4%	15.1%	35.8%	26.4%
weekly	90/10	4.4%	2.0%	5.6%	1.8%	3.1%	0.8%	3.1%	1.0%	2.3%	1.2%	1.8%	0.9%	1.7%	0.7%
	80/20	14.6%	8.1%	16.9%	9.9%	10.3%	6.3%	10.4%	6.4%	10.5%	4.9%	7.8%	4.0%	9.2%	4.0%
	70/30	32.6%	21.7%	31.4%	25.9%	21.5%	15.8%	21.0%	15.6%	21.8%	15.7%	21.3%	15.6%	23.5%	16.9%
dairy	90/10	2.7%	0.9%	3.1%	1.3%	1.8%	0.8%	1.9%	0.8%	2.2%	0.5%	2.0%	0.4%	3.0%	1.1%
	80/20	10.6%	6.2%	11.4%	7.1%	7.6%	5.1%	7.7%	5.2%	8.9%	4.3%	8.7%	4.3%	9.8%	6.2%
	70/30	24.7%	18.4%	26.0%	21.1%	19.4%	15.4%	19.5%	16.4%	21.4%	14.8%	20.1%	14.2%	22.6%	17.1%
60 mins	90/10	3.4%	1.1%	3.5%	1.0%	2.8%	0.7%	–	–	3.6%	1.3%	2.8%	0.6%	2.3%	0.8%
	80/20	11.2%	6.8%	11.0%	6.8%	9.6%	5.3%	–	–	11.9%	7.5%	10.4%	5.0%	8.6%	4.6%
	70/30	20.9%	16.3%	21.0%	16.6%	19.9%	14.8%	–	–	24.1%	18.8%	21.6%	16.1%	19.4%	13.8%
15 mins	90/10	1.8%	0.4%	1.5%	0.4%	2.3%	0.6%	–	–	1.8%	0.4%	1.6%	0.4%	1.4%	0.5%
	80/20	8.4%	4.1%	7.9%	3.9%	8.7%	4.6%	–	–	8.5%	4.2%	8.4%	4.0%	6.8%	3.3%
	70/30	19.6%	14.1%	19.0%	13.9%	19.8%	14.3%	–	–	20.9%	14.4%	20.1%	13.9%	17.4%	11.8%
5 mins	90/10	1.7%	0.4%	1.7%	0.4%	1.7%	0.4%	–	–	1.7%	0.5%	1.8%	0.5%	1.6%	0.4%
	80/20	7.8%	3.6%	7.9%	3.6%	7.9%	3.7%	–	–	7.6%	3.6%	7.9%	3.5%	6.9%	3.2%
	70/30	19.1%	12.9%	18.8%	12.9%	19.5%	13.1%	–	–	19.1%	12.9%	18.8%	12.8%	17.0%	11.3%
1 mins	90/10	1.6%	0.4%	1.6%	0.4%	1.9%	0.6%	–	–	1.8%	0.6%	1.6%	0.5%	1.5%	0.4%
	80/20	7.4%	3.4%	7.3%	3.2%	7.8%	4.1%	–	–	7.7%	3.9%	7.2%	3.4%	6.9%	3.2%
	70/30	18.1%	12.3%	18.1%	12.2%	18.7%	13.2%	–	–	18.8%	14.0%	18.1%	12.5%	17.1%	11.8%

3.4.3 Price Fluctuations

In the simulated market, an almost normal distribution was shown. The values between 1 σ and 2 σ were slightly thicker than those of the normal distribution, while those above 2 σ were slightly thinner. The distribution at Close was slightly closer to a normal distribution (Table 11).

Table 11 Price fluctuations measured in the simulated market

Number of Data	Simulation			Normal Distribution
	Standard deviation	TP	Close	
70,000	$>2\sigma, <-2\sigma$	4.4%	4.2%	
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	29.3%	28.7%	
	$<1\sigma, >-1\sigma$	66.2%	67.1%	
350,000	$>2\sigma, <-2\sigma$	4.4%	4.3%	4.6%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	29.4%	28.4%	27.2%
	$<1\sigma, >-1\sigma$	66.2%	67.3%	68.3%

In the actual market, the distribution was also close to a normal distribution, but slightly thicker above 2 σ and below 1 σ (Table 12). Expressed as a distribution diagram, the central peak was a little higher and both ends were a little thicker (fat-tail structure). This phenomenon is a known fact (Tabuchi 2005, pp 43-44) and here it is clearly evident. There were no notable differences among markets, but in timeframes, the trend became more pronounced as the timeframes expanded in the minute-timeframe. A closer look reveals that the maximum for above 2 σ was the 15-minutes, while the maximum for below 1 σ was the 60-minutes, which was common to all subjects. There was no significant difference between daily and weekly, and only the monthly was more pronounced. Generally, values measured at Close were closer to the normal distribution and the fat-tail structure was more pronounced at TP.

Table 12 Price fluctuations measured in the actual markets

		S&P500		NASDAQ		Nikkei225		TOPIX	
		TP	Close	TP	Close	TP	Close	TP	Close
monthly	$>2\sigma, <-2\sigma$	8.4%	7.5%	7.2%	8.1%	6.0%	4.8%	5.1%	5.1%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	27.8%	30.7%	29.3%	29.6%	24.2%	26.9%	28.1%	27.2%
	$<1\sigma, >-1\sigma$	64.2%	62.1%	63.6%	62.4%	69.9%	68.3%	67.2%	68.1%
weekly	$>2\sigma, <-2\sigma$	5.4%	6.2%	5.6%	5.4%	5.1%	5.5%	5.5%	5.4%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	25.3%	24.4%	28.4%	26.2%	25.5%	24.4%	24.4%	24.7%
	$<1\sigma, >-1\sigma$	69.4%	69.5%	66.0%	68.5%	69.5%	70.2%	70.1%	69.9%
dairy	$>2\sigma, <-2\sigma$	5.2%	5.2%	5.4%	5.2%	5.2%	5.0%	5.1%	4.9%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	27.1%	25.7%	26.2%	26.1%	26.7%	26.4%	26.3%	26.4%
	$<1\sigma, >-1\sigma$	67.7%	69.1%	68.5%	68.7%	68.1%	68.6%	68.6%	68.7%
60 mins	$>2\sigma, <-2\sigma$	6.2%	5.8%	6.0%	6.2%	5.8%	5.5%	–	–
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	19.7%	18.3%	18.6%	16.7%	21.9%	20.9%	–	–
	$<1\sigma, >-1\sigma$	74.1%	76.0%	75.3%	77.1%	72.3%	73.6%	–	–
15 mins	$>2\sigma, <-2\sigma$	7.0%	6.5%	7.2%	6.6%	6.3%	6.1%	–	–
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	22.5%	21.7%	21.7%	21.0%	22.1%	21.3%	–	–
	$<1\sigma, >-1\sigma$	70.5%	71.8%	71.1%	72.4%	71.6%	72.6%	–	–
5 mins	$>2\sigma, <-2\sigma$	5.9%	5.6%	5.8%	5.7%	5.6%	5.5%	–	–
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	25.1%	24.0%	24.6%	23.7%	23.9%	23.1%	–	–
	$<1\sigma, >-1\sigma$	69.1%	70.4%	69.6%	70.6%	70.4%	71.4%	–	–
1 mins	$>2\sigma, <-2\sigma$	5.4%	5.1%	5.3%	5.0%	5.4%	5.3%	–	–
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	25.9%	25.0%	25.8%	25.0%	25.3%	24.3%	–	–
	$<1\sigma, >-1\sigma$	68.7%	69.9%	68.9%	69.9%	69.3%	70.3%	–	–

		USDJPY		Crude Oil		Gold	
		TP	Close	TP	Close	TP	Close
monthly	$>2\sigma, <-2\sigma$	7.2%	6.6%	7.8%	6.3%	8.1%	7.0%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	22.4%	22.4%	27.2%	28.7%	24.4%	27.9%
	$<1\sigma, >-1\sigma$	70.4%	71.0%	65.4%	65.4%	67.4%	65.5%
weekly	$>2\sigma, <-2\sigma$	5.3%	5.3%	4.4%	4.5%	5.3%	5.1%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	26.7%	25.5%	28.6%	27.4%	27.4%	24.6%
	$<1\sigma, >-1\sigma$	68.1%	69.3%	67.0%	68.2%	67.4%	70.4%
dairy	$>2\sigma, <-2\sigma$	5.4%	5.3%	5.3%	5.1%	5.2%	5.6%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	24.9%	24.3%	25.7%	25.4%	24.9%	22.2%
	$<1\sigma, >-1\sigma$	69.7%	70.4%	69.1%	69.6%	69.9%	72.2%
60 mins	$>2\sigma, <-2\sigma$	5.6%	5.5%	5.9%	5.9%	5.8%	5.3%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	22.2%	20.5%	20.6%	19.9%	20.3%	20.3%
	$<1\sigma, >-1\sigma$	72.2%	74.0%	73.5%	74.2%	73.9%	74.4%
15 mins	$>2\sigma, <-2\sigma$	6.1%	6.0%	6.9%	6.6%	6.4%	6.1%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	23.0%	22.0%	23.3%	22.1%	23.0%	22.1%
	$<1\sigma, >-1\sigma$	70.9%	72.0%	69.8%	71.3%	70.6%	71.7%
5 mins	$>2\sigma, <-2\sigma$	5.6%	5.4%	5.9%	5.7%	5.8%	5.4%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	24.1%	23.5%	24.0%	23.2%	24.5%	24.2%
	$<1\sigma, >-1\sigma$	70.3%	71.2%	70.0%	71.0%	69.7%	70.4%
1 mins	$>2\sigma, <-2\sigma$	5.4%	5.4%	5.5%	5.4%	5.4%	5.4%
	$1\sigma \sim 2\sigma, -2\sigma \sim -1\sigma$	24.6%	23.5%	24.6%	23.4%	25.4%	24.0%
	$<1\sigma, >-1\sigma$	69.9%	71.1%	69.9%	71.2%	69.2%	70.7%

3.5 ANALYSIS OF THE NUMBER OF CONSECUTIVE RISES AND FALLS

Table 13 left shows the results of counting the number of times in 350,000 simulated markets (Close). The results show that the probability of rises and falls is almost 1/2, which can be called a random walk. When the same data is counted at TP, the result is shown in Table 13 right, showing that the percentage of "0" time decreased significantly, and the probability of "above 1" times increased at all counts.

Table 13 Number of consecutive rises and falls and its percentage measured in the simulated market

Consecutive Counts	number of events	percentage
0	174,981	50.0%
1	87,272	24.9%
2	43,804	12.5%
3	21,847	6.2%
4	10,945	3.1%
5	5,554	1.6%
6	2,761	0.8%
7	1,393	0.4%
8	713	0.2%
9	361	0.1%
10	183	0.1%
11	99	0.0%
12	47	0.0%
13	21	0.0%
14	12	0.0%
>=15	7	0.0%
Total	350,000	100.0%

Consecutive Counts	number of events	percentage
0	143,892	41.1%
1	87,295	24.9%
2	50,078	14.3%
3	29,043	8.3%
4	16,730	4.8%
5	9,678	2.8%
6	5,566	1.6%
7	3,227	0.9%
8	1,847	0.5%
9	1,083	0.3%
10	642	0.2%
11	391	0.1%
12	220	0.1%
13	131	0.0%
14	72	0.0%
>=15	105	0.0%
Total	350,000	100.0%

Table 14 are the examples of actual markets. Only a few examples are presented, because the results were virtually indistinguishable in any market or timeframe, except for the monthly, for which data were scarce When measured at Close, the rate of occurrence was almost halved for every 1 count in any market or timeframe, which was very similar to the simulated market. However, when observed in detail, there were some areas where a slight fluctuation in probability could be detected. The left and middle are with a little visible fluctuation and the right is with almost no fluctuation. In the DISCUSSION section, the results are tabulated in a different way to explore how much the fluctuations affect the trade.

Table 14 Number of consecutive rises and falls and its percentage measured in the actual markets

Nasdaq (Weekly)

Consecutive Counts	number of events	percentage
0	762	48.7%
1	373	23.8%
2	189	12.1%
3	115	7.4%
4	63	4.0%
5	33	2.1%
6	16	1.0%
7	7	0.4%
8	3	0.2%
9	2	0.1%
10	1	0.1%
11	0	0.0%
12	0	0.0%
13	0	0.0%
14	0	0.0%
>=15	0	0.0%
Total	1,564	100.0%

S&P500 (Daily)

Consecutive Counts	number of events	percentage
0	3,904	51.7%
1	1,907	25.2%
2	972	12.9%
3	437	5.8%
4	197	2.6%
5	84	1.1%
6	32	0.4%
7	13	0.2%
8	4	0.1%
9	1	0.0%
10	1	0.0%
11	1	0.0%
12	0	0.0%
13	0	0.0%
14	0	0.0%
>=15	0	0.0%
Total	7,553	100.0%

Nikkei225 (60mins)

Consecutive Counts	number of events	percentage
0	2,908	50.2%
1	1,447	25.0%
2	710	12.3%
3	345	6.0%
4	183	3.2%
5	91	1.6%
6	46	0.8%
7	26	0.4%
8	14	0.2%
9	7	0.1%
10	3	0.1%
11	3	0.1%
12	1	0.0%
13	1	0.0%
14	1	0.0%
>=15	3	0.1%
Total	5,789	100.0%

DISCUSSION

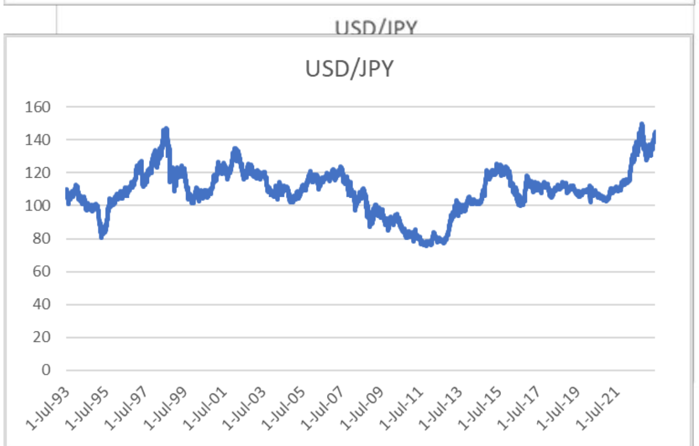
4.1 MARKETS TO BE ANALYZED

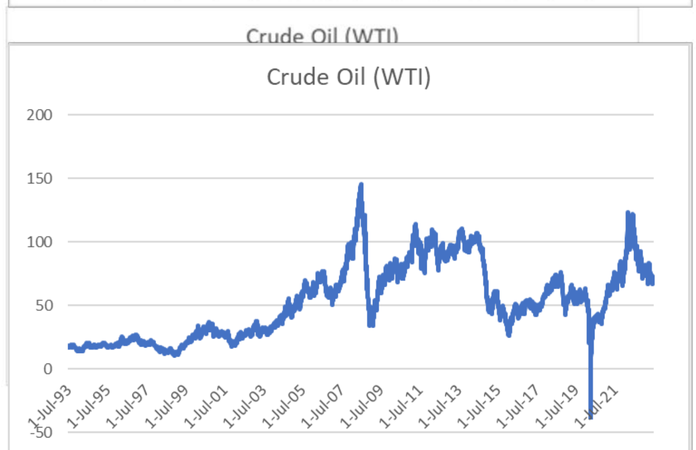
To begin, the price movements of each market over a 30-year period are shown in a small graph (Figure 3) *10. The characteristics of the price movements ensure diversity. This suits the purpose of this thesis, which is to analyze the similarity of the markets. Figure 4 is a graph for each market for the year 2022, using 60-minutes timeframe.

Figure 3 Price movements of each market over 30 years (line graph of daily Close)


Nikkei 225
40,000.00
35,000.00
30,000.00
25,000.00
20,000.00
15,000.00
10,000.00
5,000.00
0.00
1-Jul-93
1-Jul-95
1-Jul-97
1-Jul-99
1-Jul-01
1-Jul-03
1-Jul-05
1-Jul-07
1-Jul-09
1-Jul-11
1-Jul-13
1-Jul-15
1-Jul-17
1-Jul-19
1-Jul-21

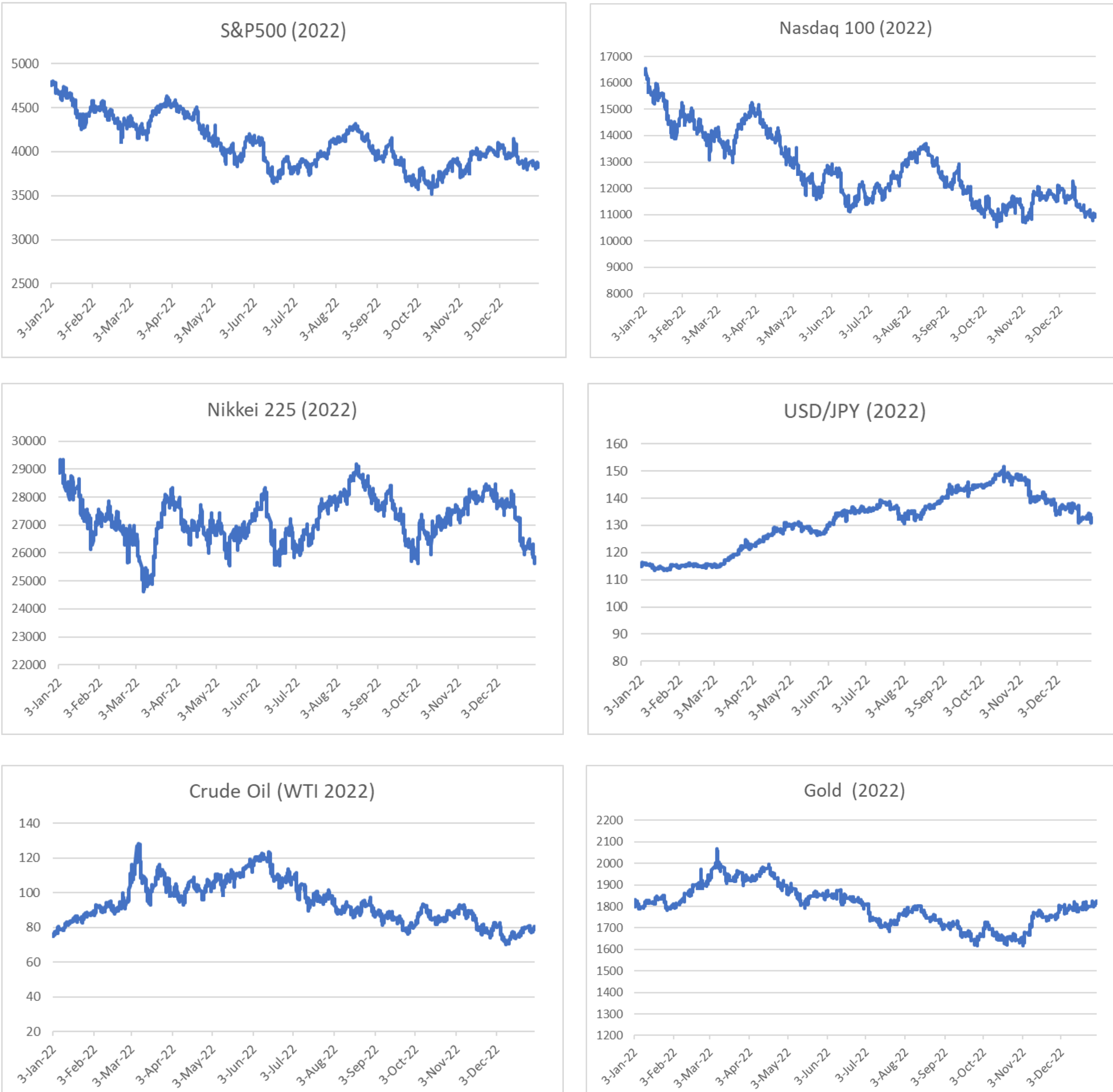

TOPIX
2,500.00
2,000.00
1,500.00
1,000.00
500.00
0.00
1-Jul-93
1-Jul-95
1-Jul-97
1-Jul-99
1-Jul-01
1-Jul-03
1-Jul-05
1-Jul-07
1-Jul-09
1-Jul-11
1-Jul-13
1-Jul-15
1-Jul-17
1-Jul-19
1-Jul-21


USD/JPY
160
140
120
100
80
60
40
20
0
1-Jul-93
1-Jul-95
1-Jul-97
1-Jul-99
1-Jul-01
1-Jul-03
1-Jul-05
1-Jul-07
1-Jul-09
1-Jul-11
1-Jul-13
1-Jul-15
1-Jul-17
1-Jul-19
1-Jul-21


Crude Oil (WTI)
200
150
100
50
0
-50
1-Jul-93
1-Jul-95
1-Jul-97
1-Jul-99
1-Jul-01
1-Jul-03
1-Jul-05
1-Jul-07
1-Jul-09
1-Jul-11
1-Jul-13
1-Jul-15
1-Jul-17
1-Jul-19
1-Jul-21


Gold
2500
2000
1500
1000
500
0
1-Dec-99
1-Dec-01
1-Dec-03
1-Dec-05
1-Dec-07
1-Dec-09
1-Dec-11
1-Dec-13
1-Dec-15
1-Dec-17
1-Dec-19
1-Dec-21

Figure 4 Price movements of each market during 2022 (line graph of 60-minutes'Close)



This section presents how similarities and differences can be found in the above completely different markets and in various timeframes, using the simulated market as a benchmark.

4.2 GVR

ATR, devised by J.W. Wilder Jr. is a technical indicator measuring market volatility. It shows the "average of the true price range". For the average, 14 was used following the inventor. Since ATR uses the previous Close, High and Low of the current bar, GVR greater than 100 indicates that the price fluctuation between the previous bar and the current bar is greater than ATR(14). ATR tends to have a larger value than GVR because ATR also takes into account the range in the current bar. In the measurement of the simulated market, the mean value of GVR was 50 at TP and about 90% of all data settled within 100. The significance of using ATR for the divisor is, first, that it allows markets with different prices and currencies to be directly compared using the same yardstick, making it a powerful tool for measuring similarity. ATR is calculated based on the price itself, so it is not directly comparable for different markets and timeframes. The same is true for the price fluctuation between the previous bar and the current one. This can be generalized as a magnification by dividing the price fluctuation by ATR for direct comparison. The second reason is to mitigate the characteristics of ATR, which directly reflects the effects of rises and falls in the current bar, as Ehlers defines "Noise in trading is the average of the daily trading ranges" (Ehlers 2001, p 98).

The expectation before calculating was that GVR would not only vary considerably from market to market and timeframe to timeframe, but also exceed 50, relative to the average value of the simulated market. Thus, the constancy in the 40s in almost all markets and timeframes was unexpected (Tables 1 and 2 in the previous chapter).

Next, a detailed discussion about GVR is added.

First, the difference between the measured values at TP and at Close means that the range of change at Close is larger than at TP. In the simulated market, the mean GVR was 63 at Close compared to 50 at TP, which was more than 20% larger. In the actual market, the difference was almost the same, the values changed but the mutual relationship remained the same*[11]. In addition, the value of 50 is easy to understand. Thus, the discussion here is based on the values measured at TP.

Second, consider the fact that GVR in the actual market is smaller than that of simulated market. This indicates that the actual market has milder price fluctuations (compared to the previous bar) than the random-walking market. The GVR compares the current price fluctuation to the recent average price fluctuation. It is usually in the 40s and the probability of a value above 100 is less than 10% in any market or timeframe, both smaller than those of the simulated market.

Third, there is a fact that not only are the values of above-daily timeframes larger than those of minute-timeframes, but also exceptionally large values of around 50 (comparable to the simulated market) are observed in the above-daily values of the U.S. and Japanese stock indices. One reason for this is very likely to derive from the large gaps due to the influence of other markets outside of the session hours. The situation differs from that of FX, etc., which is continuously traded for nearly 24 hours. Therefore, the values for the case where nighttime session of stock indices is also included are reported in Endnotes*[12].

The above discussion indicates that the relative magnitudes of price fluctuations represented by GVR are generally similar among the various markets and timeframes*[13]. In addition, there are differences between stock indices and other markets at the daily and longer timeframes, while other differences are small. It is also shown that small differences with certain trends can be observed among different timeframes*[14].

4.3 GDMA

This indicator is calculated by dividing the deviation from a moving average by ATR. It expresses, as a percentage, how many magnifications the deviation is from the average price range in the market. As with GVR, ATR is used as a divisor to allow direct comparison between markets. When graphed, GDMA shows similar behavior to the moving average deviation ratio. In terms of value distribution, GDMA that exceeds 300 are approximately 5% (equivalent to almost 2σ (4.6%) for a normal distribution) in most cases in all markets and timeframes, so it is a stable indicator because it provides an approximate probability in advance for judging trends and sudden price excesses.

GDMA in the stock indices, especially in the two U.S. stock indices, are large in the 60-minute or longer timeframe, equal to or even larger than the 130% (standard value in the simulated market). The larger value for longer timeframes suggests that the trends are more long-term valid. This is deeply related to the analysis in the next section (DoMA), which will be described in 4.4.

4.4 DoMA

Durability of Moving Average measures the degree to which price fluctuations are sustained when they take a certain direction. It calculates the average number of bars required to change direction of EMA.

First, since DoMA of 5EMA for any market shows no difference from that of the simulated market, it seems that the short-term exponential moving average is the same as measuring a random-walking prices and not measuring what can be called a trend*[15].

On the other hand, for the 20 and 50 EMAs, DoMA are larger than for the simulated market as the timeframe expands in all markets: slightly for the 20, but clearly for the 50. This suggests that even artificial market with random walk can look trend-like, but in real "human-involved" markets, the persistence of the trend increases due to human bias. Furthermore, as with the GDMA, particularly large values are observed in the U.S. stock indices at 20 and 50 EMA of the daily or above timeframes. Those of Japan are also somewhat larger than those of the non-stock index markets. Relating this to 4.3, it can be said that trends tend to persist longer in stock indices than in other markets and deviations from moving averages also tend to be larger*[16].

ββIn summary, we can conclude that 1) the larger the timeframe and the longer the period over which price direction is measured, the more meaningful direction can be captured; 2) this is especially true for stock indices; and 3) a direction has more staying power in any market than in simulated market. Regarding the market similarity, all markets are similar at the minute timeframe level, while at the daily level and above, differences are measured between stock indices and other markets.

4.5 ANALYZING THE DISTRIBUTION OF REPRESENTATIVE TECHNICAL INDICATORS AND PRICE FLUCTUATIONS BASED ON THEIR STANDARD DEVIATIONS

4.5.1 Bollinger bands and Price Fluctuations

Bollinger bands are invented by John A. Bollinger in 1980s. At the beginning of this section, the existence of a misunderstanding about the relationship between Bollinger bands and the distribution of price fluctuations is described. It is the range of the price fluctuation that makes the distribution similar to a normal distribution, not the price itself. It is clear from the results in 3.4.1 and 3.4.3, and has already been pointed out in 2004 (Kimura 2004 The Nippon Technical Analysis Compendium, pp 169-170). However, the misunderstanding that "about 95% of prices are expected to settle within the 2σ line of the Bollinger bands" is still widely believed*[17]. It is hoped that this thesis will also help to make people aware of this misconception.

4.5.2 Bollinger bands Analysis

The appearance of above 2σ of the Bollinger bands is still a point of interest. On the minute-timeframes, the rate of appearance increases slightly as the timeframe size expands. However, the maximum difference between the 1-minute and 60-minutes timeframes is less than 2%, so it is difficult to say whether this is a useful difference. The percentage above 2 σ β also tends to increase as the timeframe expands for daily and longer timeframes, and the values of monthly-timeframes are noticeably different among the markets and countries. The percentage above 2σ increases significantly for the U.S. stock indices, crude oil and gold, while it does not increase much or rather decreases for the Japanese stock indices and USD-JPY. This is one aspect of the market's characteristics. It is also considered useful in trading to focus on markets where values which are far away from the standard value of 13% measured in the simulated market.

4.5.3 RSI

RSI was invented by J. Welles Wilder, Jr. in 1978. To observe the behavior of RSI in any markets, the percentage exceeding thresholds set at 90/10, 80/20, and 70/30 was examined. The thresholds will be easier to adjust if it is known in advance what percentage of cases exceed them. The results of this measurement can be used for the adjustment. For example, depending on the market or timeframe, It might be a good idea to determine the threshold at the point where the percentage exceeding it will be 2σ (about 5%). Since RSI is unimodally distributed (Matoba 2004 The Nippon Technical Analysis Compendium, pp 254-255), it makes sense to determine the threshold by a percentage based on the standard deviation. In this idea, if using the daily Close of the Nikkei 225, 80/20 will be acceptable, but for the weekly TP of the S&P 500, 80/20 will be too frequent, and a value closer to 90/10 will be better.

4.5.4 Price fluctuations

The distribution of price fluctuations measured in the simulated market deviates slightly from the normal distribution. Since the continuous sequence of each value itself in the simulated market follows a normal distribution exactly, the act of cutting the continuous data by 10 (Close) and comparing the Close with the previous Close is presumed to be the cause of this discrepancy. Although the mechanism could not be elucidated in this thesis, it is interesting to note that the percentage of above-2σ values decreased in the simulated market relative to the normal distribution, whereas above-2 σ increased in the actual market. The fat-tail structure can be seen even in the 1-minute timeframe, with the above-2 σ increasing as the timeframe expands (the largest in the 15-minute timeframe). While the discontinuity between 60-minute and daily timeframe is aforementioned *[12], it should be noted that the 1-minute and daily timeframes show nearly indistinguishable values and are the closest to a normal distribution of all timeframes. In addition, it can be said that the larger the timeframe, whether it is a minute or a day, the larger the distribution for the tail, and thus the more extreme the price fluctuation likely occurs.

Note that while Bollinger bands and RSI have larger above-2σ percentages when measured at TP than at Close, this is not necessarily the case for price fluctuations, especially for stock indices. Nor did the trends differ between U.S. stock indices and others, as observed elsewhere.

The above analyses of the Bollinger bands, RSI, and price fluctuations all show a tendency to be thicker for the tail of the distribution than the simulated market, and the trend also becomes clearer as the timeframe expands. Furthermore, differences are observed between stock indices and the rest of the markets in daily or above timeframes, except for price fluctuations. In price fluctuations, there is a strong similarity among all markets, including stock indices. From the above, a strong indication about the similarities and differences in the markets is obtained in this section 4.5, as in previous sections.

4.6 ANALYSIS OF THE NUMBER OF CONSECUTIVE RISES AND FALLS

In the simulated market, the probability of a rise or fall is almost strictly 1/2, however, roughly speaking, even in the actual market, the probability is closer to 1/2. It was somewhat surprising that the probability is almost 1/2 even for stock indices with a strong long-term upward trend. However, there are some cases where the probability deviates slightly from 1/2, and furthermore, not only the probability but the price range should be taken into account. Therefore, the results of trend-follow and contrarian trading according to the number of consecutive rises and falls are presented on table 15 and 16. The trading are taken price ranges into account and 1.00 is the neutral value*[18]. The implication of values is the same as profit factor, which does not include spreads or commissions. The true ratio of win and lose is calculated by multiplying the price fluctuations by the number of rises or falls. If it exceeds 1.00, it is a win. Considering the frequency of occurrence, no more than 5 consecutive times are included.

In the simulated market, both trend-follow and contrarian trading were close to 1.00, indicating that a random walk could be represented (Table 15).

Table 15 Number of consecutive rises and falls and winning percentage in the simulated market

Simulation

Number of data	7,500		24,000		70,000		350,000	
Consecutive Counts	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian
0	0.92	1.08	1.00	1.00	0.98	1.02	0.99	1.01
1	1.06	0.94	1.09	0.91	1.00	1.00	1.00	1.00
2	0.99	1.01	0.95	1.05	1.01	0.99	1.00	1.00
3	1.04	0.96	0.95	1.06	1.00	1.00	0.99	1.01
4	0.91	1.10	0.96	1.05	0.98	1.02	0.97	1.03
5	1.00	1.00	1.05	0.95	1.02	0.98	0.96	1.04

The results for the actual markets are shown in Table 16. Some extreme values were seen in the monthly timeframes. A common phenomenon with one exception were found in each market where the number of consecutive times was 2 or 3 for the weekly and daily timeframes. For example, if the same direction appeared for two consecutive weeks, the third week was preferable to follow the direction (with the exception of S&P 500), and the fourth week was preferable to reverse the direction. This seems to be an anomaly. Or the "gambler's fallacy" of behavioral finance theory might be at work here. When the same direction appears several times, they "underestimate the trend" and go against it (Tabuchi, 2005, p. 62). On the other hand, there are no extreme values seen in the minute-timeframes. As the timeframe gets smaller, they are approaching 1.00, but there might be somewhat distinctive information. The stock indices have a slight advantage of trend-follow up to three times in the 1-minute timeframe and a slight advantage of contrarian in the 5-minute timeframe. However, this might be an error.

It is found that all markets are close to 1/2 in terms of mere probability of a rise and fall, but when the price fluctuation is taken into account, deviations from 1.00 occur, and some of the trends are common to the markets.

Table 16 Number of consecutive rises and falls and winning percentage in the actual markets

S&P500 Close

	Monthly		Weekly		Daily		60 mins		15 mins		5 mins		1 min	
Consecutive Counts	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian
0	0.74	1.35	0.87	1.15	0.95	1.05	0.93	1.07	1.01	0.99	0.98	1.02	1.04	0.96
1	0.85	1.17	0.83	1.21	1.01	0.99	0.84	1.19	1.04	0.97	0.96	1.04	1.01	0.99
2	1.92	0.52	0.83	1.21	0.80	1.25	0.87	1.14	1.01	0.99	0.91	1.10	1.00	1.00
3	2.21	0.45	0.82	1.21	0.69	1.44	1.16	0.86	0.98	1.02	0.92	1.09	0.95	1.05
4	0.67	1.50	0.79	1.26	0.75	1.34	0.93	1.08	0.81	1.24	0.95	1.06	0.96	1.05
5	1.26	0.79	1.48	0.68	0.56	1.80	0.79	1.27	1.12	0.89	0.92	1.08	0.89	1.12

NASDAQ Close

	Monthly		Weekly		Daily		60 mins		15 mins		5 mins		1 min	
Consecutive Counts	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian
0	0.87	1.15	0.92	1.08	0.99	1.01	0.99	1.01	1.01	0.99	0.99	1.01	1.05	0.95
1	1.09	0.92	0.89	1.12	1.04	0.96	0.87	1.14	1.04	0.96	0.99	1.01	1.03	0.97
2	0.90	1.11	1.41	0.71	0.86	1.16	0.81	1.24	1.07	0.94	0.96	1.04	1.00	1.00
3	2.11	0.47	1.09	0.92	0.77	1.30	0.94	1.06	0.93	1.07	0.87	1.15	0.95	1.06
4	0.65	1.54	1.09	0.92	0.59	1.71	0.98	1.02	0.88	1.14	0.96	1.04	1.02	0.98
5	2.81	0.36	0.74	1.35	0.68	1.48	1.33	0.75	1.20	0.83	0.98	1.03	0.91	1.10

Nikkei225 Close

	Monthly		Weekly		Daily		60 mins		15 mins		5 mins		1 min	
Consecutive Counts	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian
0	0.84	1.18	0.89	1.12	0.95	1.06	1.00	1.00	1.01	0.99	0.98	1.02	1.03	0.97
1	0.75	1.34	1.01	0.99	0.97	1.03	0.91	1.10	1.03	0.97	0.98	1.02	1.04	0.96
2	1.49	0.67	1.36	0.73	0.90	1.11	0.87	1.15	1.00	1.00	0.96	1.04	1.03	0.97
3	1.58	0.63	0.89	1.12	0.72	1.39	1.25	0.80	1.05	0.96	0.92	1.09	0.98	1.02
4	1.08	0.92	1.09	0.92	1.29	0.78	0.77	1.31	0.95	1.05	1.01	0.99	1.00	1.00
5	2.92	0.34	0.78	1.29	1.28	0.78	1.20	0.83	1.01	0.99	0.91	1.10	0.91	1.10

TOPIX Close

	Monthly		Weekly		Daily		60 mins		15 mins		5 mins		1 min	
Consecutive Counts	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian
0	0.84	1.19	0.97	1.03	1.11	0.90	–	–	–	–	–	–	–	–
1	0.88	1.14	1.05	0.95	1.22	0.82	–	–	–	–	–	–	–	–
2	2.06	0.49	1.13	0.89	1.04	0.97	–	–	–	–	–	–	–	–
3	2.06	0.49	0.91	1.10	0.93	1.07	–	–	–	–	–	–	–	–
4	0.82	1.22	0.94	1.06	1.26	0.79	–	–	–	–	–	–	–	–
5	1.01	0.99	2.47	0.40	1.12	0.89	–	–	–	–	–	–	–	–

USDJPY Close

	Monthly		Weekly		Daily		60 mins		15 mins		5 mins		1 min	
Consecutive Counts	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian
0	0.84	1.19	0.89	1.12	1.03	0.97	1.09	0.92	0.98	1.02	1.01	0.99	1.03	0.97
1	1.43	0.70	0.89	1.12	0.92	1.08	1.10	0.91	1.03	0.97	1.01	0.99	1.03	0.97
2	0.77	1.30	1.03	0.97	0.90	1.11	1.26	0.79	0.90	1.11	0.97	1.04	1.01	0.99
3	2.23	0.45	0.96	1.05	1.01	0.99	1.18	0.85	1.05	0.95	0.99	1.01	0.96	1.04
4	0.79	1.27	1.03	0.97	0.85	1.18	0.84	1.19	0.99	1.01	0.94	1.06	0.93	1.07
5	1.34	0.75	1.60	0.63	0.99	1.01	0.87	1.15	1.00	1.00	0.89	1.13	0.86	1.16

Crude Oil Close

	Monthly		Weekly		Daily		60 mins		15 mins		5 mins		1 min	
Consecutive Counts	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian
0	1.26	0.79	1.17	0.85	1.02	0.98	0.93	1.08	0.98	1.02	0.97	1.03	1.00	1.00
1	0.93	1.08	0.86	1.16	0.98	1.02	0.95	1.05	1.02	0.98	0.97	1.03	0.96	1.04
2	1.50	0.67	1.26	0.80	0.85	1.18	1.04	0.97	0.99	1.01	1.03	0.97	0.97	1.03
3	0.72	1.40	0.74	1.36	0.90	1.11	0.90	1.11	0.84	1.19	0.92	1.09	0.99	1.01
4	2.67	0.37	1.84	0.54	1.00	1.00	1.10	0.91	0.92	1.09	1.03	0.97	0.97	1.03
5	1.99	0.50	1.21	0.83	1.75	0.57	0.76	1.32	0.90	1.11	0.91	1.10	0.97	1.04

Gold Close

	Monthly		Weekly		Daily		60 mins		15 mins		5 mins		1 min	
Consecutive Counts	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian	Trend follow	Contrarian
0	1.14	0.88	1.04	0.96	0.95	1.05	1.15	0.87	0.97	1.04	0.96	1.05	1.01	0.99
1	0.93	1.08	1.00	1.00	1.00	1.00	0.93	1.07	0.97	1.03	0.95	1.06	0.98	1.02
2	1.12	0.89	1.50	0.67	0.85	1.17	0.96	1.04	0.95	1.05	0.95	1.05	0.96	1.04
3	0.91	1.10	0.61	1.65	0.84	1.19	0.82	1.22	1.20	0.83	0.95	1.05	0.91	1.09
4	0.57	1.77	0.95	1.05	1.08	0.92	1.01	0.99	1.02	0.98	0.99	1.01	0.97	1.04
5	0.94	1.07	0.64	1.57	1.70	0.59	1.06	0.94	0.91	1.10	1.00	1.00	1.03	0.97

Although Close has used to analyze consecutive rises and falls in this section considering the real trading, other prices, such as High, Low and TP, are also analyzed at Table 17. Calculated using S&P 500's daily timeframe, the left two tables are almost indistinguishable, although the S&P 500's 30-year long-term uptrend is clear. From this it can be said that when a high or low is renewed, the probability that it will be renewed on the next bar is greater than 1/2. The probability of no more than one renewal is about 44%, and the following each renewal is more than half of the probability of the previous one. This result is even more pronounced when measured in TP.

Table 17 Number of consecutive rises and falls and its probability in S&P500 (Daily High, Low, TP)

S&P Daily_High

Consecutive Counts	number of events	percentage
0	3,352	44.4%
1	1,869	24.7%
2	1,047	13.9%
3	590	7.8%
4	330	4.4%
5	180	2.4%
6	89	1.2%
7	45	0.6%
8	25	0.3%
9	12	0.2%
10	5	0.1%
11	4	0.1%
12	2	0.0%
13	2	0.0%
14	1	0.0%
>=15	0	0.0%
Total	7,553	100.0%

S&P Daily_Low

Consecutive Counts	number of events	percentage
0	3,334	44.1%
1	1,921	25.4%
2	1,052	13.9%
3	546	7.2%
4	317	4.2%
5	171	2.3%
6	93	1.2%
7	46	0.6%
8	30	0.4%
9	14	0.2%
10	11	0.1%
11	9	0.1%
12	6	0.1%
13	2	0.0%
14	1	0.0%
>=15	0	0.0%
Total	7,553	100.0%

S&P Daily_TP

Consecutive Counts	number of events	percentage
0	3,130	41.4%
1	1,905	25.2%
2	1,092	14.5%
3	634	8.4%
4	371	4.9%
5	190	2.5%
6	106	1.4%
7	55	0.7%
8	30	0.4%
9	15	0.2%
10	11	0.1%
11	6	0.1%
12	5	0.1%
13	2	0.0%
14	1	0.0%
>=15	0	0.0%
Total	7,553	100.0%

Based on the above discussion, the analysis of the number of consecutive rises and falls in Close shows that all markets are similar including the simulated market, with no significant difference in timeframes. This is the most striking example of similarity, the theme of this paper. However, when aggregating the data considering the price fluctuation, it can be said that a few characteristics common to each market, and different from simulated market, can be extracted.

4.7 APPLICATION TO TRADINGYSTEMS

4.7.1 Evaluation Methods

Finally, three samples of trading systems based on the previous results and discussions are presented and evaluated. Along with profit/loss, number of trading and profit factor, the smoothness of the profit/loss curve and the size of drawdowns are visually verified *19 *20.

4.7.2 Application 1: Arbitrage Trading Using GVR

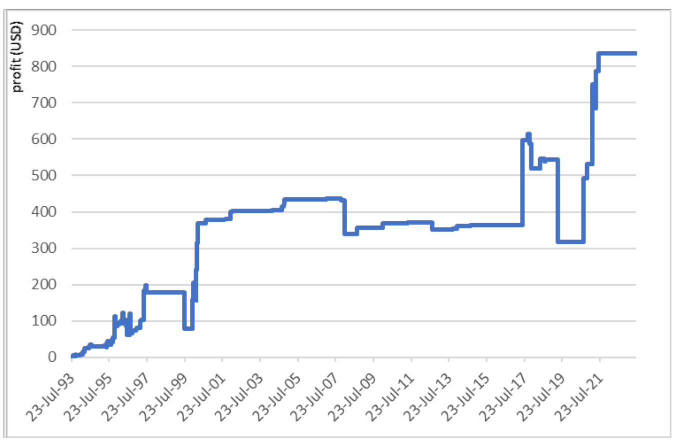
Utilizing the characteristics of GVR's ability to detect extreme price fluctuations, two entries are made at the timing of extreme value on one market and normal value on another in two highly correlated markets. Using daily timeframes of S&P 500 and Nasdaq, if one has a GVR above 100 and another has below the half, sell the one above 100 and buy the another. After the next day, the rule is set to close both trades if the overall profit is gained, and cut the loss if any profit was not gained by the end of the third day*21 (Table 18, Figure 5). Only Close is used. The PF and win rate are good and the objective seems to be met, but the low frequency, long stagnation periods and a large drawdown must be improved.

Table 18 Arbitrage trading using GVR

win	78
lose	28
win(USD)	1,565.4
lose(USD)	-918.9
Profit Factor	1.70
Average Trading Days	1.8

Maximum win	219.3
Maximum lose	-225.4

Figure 5 Arbitrage trading of S&P500 and Nasdaq using GVR



4.7.3 Application 2: Trend-follow and Contrarian Trading using GDMA and RSI

Using the daily Close of each market, a trend-follow entry is made where the GDMA is very small and moves along the direction the price is heading, closed when the GDMA is a little past its standard value. A contrarian entry is made when the GDMA is very large and close when it shrinks to a predetermined value. The GDMA for entry and exit decisions are adjusted to three types, as shown in Table 19, based on the probability of occurrence of above-300 in Table 4. In addition, RSI(14) at Close is used as a filter. In the case of a trend-follow, RSI should also be along the direction of price, and in the case of a contrarian, it should be above 85 for selling and below 15 for buying. For RSI, each market is in the same condition. Table 20 and Figure 6 show that the average trading days and the number of trading are close in each market, thus the adjustment of parameters is generally reasonable.

The overall win rate is probably the strong point of this system. Although this system does not work in some markets, there are no very bad ones.*22 However, the long periods of stagnation, even with good results, were an issue. The contrarian trading is too selective in terms of entry points, resulting in very infrequent trading in all markets.

Table 19 GDMA parameter settings (displayed in 1/100)

	Trend follow		Contrarian	
	entry	exit	entry	exit
S&P500	<0.5	>1.5	>3.0	<2.0
Nasdaq	<0.5	>1.5	>3.0	<2.0
Nikkei225	<0.5	>1.5	>3.5	<2.0
TOPIX	<0.5	>1.5	>3.5	<2.0
USD/JPY	<0.5	>1.0	>2.5	<2.0
Crude Oil	<0.5	>1.0	>2.5	<2.0
Gold	<0.5	>1.0	>2.5	<2.0

Table 20, Figure 6 Trend-follow and contrarian trading using GDMA and RSI

S&P500 Total

win	125		
lose	71		
win (USD)	5,295.13	Maximum win	216.50
lose (USD)	−3,824.78	Maximum lose	−250.88
Profit Factor	1.38		
Average Trading Days	10.46		

(contrarian)

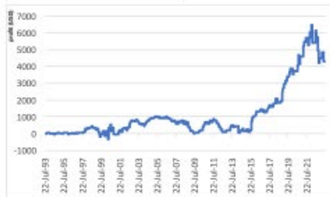
win	19		
lose	10		
win (USD)	545.51	Maximum win	205.08
lose (USD)	−107.16	Maximum lose	−46.01
Profit Factor	5.09		
Average Trading Days	5.48		

Nasdaq Total

win	138		
lose	78		
win (USD)	16,898.47	Maximum win	741.37
lose (USD)	−12,720.11	Maximum lose	−1,108.85
Profit Factor	1.33		
Average Trading Days	9.27		

(contrarian)

win	21		
lose	8		
win (USD)	1,679.94	Maximum win	598.34
lose (USD)	−864.58	Maximum lose	−362.03
Profit Factor	1.94		
Average Trading Days	7.68		

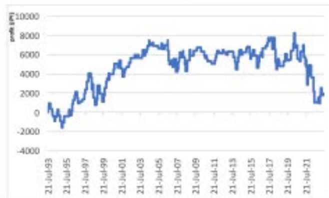


Nikkei225 Total

win	109		
lose	82		
win (JPY)	55,220.32	Maximum win	1,495.92
lose (JPY)	−53,851.75	Maximum lose	−1,529.09
Profit Factor	1.03		
Average Trading Days	10.42		

(contrarian)

win	7		
lose	4		
win (JPY)	2,426.91	Maximum win	1,090.31
lose (JPY)	−1,721.02	Maximum lose	−1,125.43
Profit Factor	1.41		
Average Trading Days	9.73		



TOPIX Total

win	104		
lose	81		
win (JPY)	3,703.17	Maximum win	111.56
lose (JPY)	−3,766.09	Maximum lose	−192.77
Profit Factor	0.98		
Average Trading Days	9.50		

(contrarian)

win	9		
lose	7		
win (JPY)	137.48	Maximum win	56.16
lose (JPY)	−349.41	Maximum lose	−192.77
Profit Factor	0.39		
Average Trading Days	9.06		

Table 20, Figure 6 Trend-follow and contrarian trading using GDMA and RSI (continued)

USD/JPY Total

win	150		
lose	117		
win (JPY)	210.70	Maximum win	5.32
lose (JPY)	−223.17	Maximum lose	−5.13
Profit Factor	0.94		
Average Trading Days	9.13		

(contrarian)

win	11		
lose	9		
win (JPY)	8.43	Maximum win	2.20
lose (JPY)	−12.25	Maximum lose	−4.10
Profit Factor	0.69		
Average Trading Days	6.72		

Crude oil Total

win	170		
lose	103		
win (USD)	375.86	Maximum win	15.00
lose (USD)	−334.78	Maximum lose	−11.36
Profit Factor	1.12		
Average Trading Days	6.96		

(contrarian)

win	14		
lose	5		
win (USD)	25.12	Maximum win	15.00
lose (USD)	−14.79	Maximum lose	−8.48
Profit Factor	1.70		
Average Trading Days	4.89		

Gold Total

win	146		
lose	78		
win (USD)	3,280.40	Maximum win	141.60
lose (USD)	−2,371.10	Maximum lose	−86.80
Profit Factor	1.38		
Average Trading Days	7.75		

(contrarian)

win	15		
lose	12		
win (USD)	171.30	Maximum win	33.80
lose (USD)	−237.50	Maximum lose	−50.50
Profit Factor	0.72		
Average Trading Days	5.44		

4.7.4 Application 3: Trading Multiple Stock Indices Using Anomalies Appearing in the Number of Consecutive Rises and falls

This is a simple logic to make a contrarian position after three consecutive ups or downs, and close it at the Close of the next day, using the anomaly found in Section 4.6, which is common to each market. This application is designed as a basket trading style. Four markets are selected, one each from stock indices, commodities, and FX representing the U.S. and Japan. The lots are multiplied based on the prices and currencies of each market. Japanese yen was converted to U.S. dollars at the rate of the closing day, and results are presented in U.S. dollars (Table 21, Figure 7). Including underperforming markets, the advantage of basket is utilized and the profit and loss trends are passably smooth. The results are in line with the anomaly read from the analysis.

Table 21, Figure 7 Trading using anomalies appearing in the number of consecutive rises and falls

S&P500 (lot:1)		CrudeOil (lot:10)		Nikkei225 (lot:10)		USD/JPY (lot:1000)	
Win	240	Win	219	Win	230	Win	219
Lose	197	Lose	221	Lose	192	Lose	207
Win (USD)	2985.90	Win (USD)	1874.40	Win (JPY)	387381.30	Win (JPY)	120312.00
Lose (USD)	−2175.31	Lose (USD)	−1816.60	Lose (JPY)	−290311.30	Lose (JPY)	−119864.00
PF	1.37	PF	1.03	PF	1.33	PF	1.00

Where the line is interrupted, it is a Saturday, Sunday, or holiday.

4.8 RESEARCH ISSUES TO BE SOLVED

For many indicators in this thesis, 1-minute timeframe and the simulated market were almost indistinguishable. However, the actual market was moving away from the simulated market with a certain trend as the timeframe expanded. Also, with moving averages, the 5-EMA was indistinguishable from the simulated market no matter what it was applied to, but not for the 20 or 50 periods. There must be an essential fact lurking in this mechanism that distinguishes the random walk from the actual market. On this very point, further analyses are needed.

CONCLUSION

5.1 SIMILARITY OF THE MARKETS

For different markets and timeframes, this thesis proposes and analyzes methods to measure across different markets and timeframes from four perspectives: volatility, moving average durability, deviation and distribution of representative technical indicators and price fluctuations, and continuous rises and falls. The results show that, with respect to the subject of this thesis, similarities are strongly suggested if the markets and timeframes are different, and also there are commonalities in the ways in which the actual market differs from the simulated market. Therefore, in a larger sense, this thesis concludes that the similarity is quite strong. In the details, in terms of market type, certain differences are observed between stock indices and other markets, and in terms of timeframes, values slightly increase almost regularly as timeframe expands. Therefore, it can be concluded that there are certain patterns in the differences of markets and timeframes.

5.2 DIFFERENCES BETWEEN ACTUAL MARKET AND RANDOM WALKING SIMULATED MARKET

A simulated market, where price fluctuations follow a normal distribution, is very similar to actual markets when displayed on a chart. The differences are examined on each of the perspectives of this thesis and it is found that quantitatively measurable differences exist in all of them. While there are few differences only in the probability of rises and falls, a difference appears when the price fluctuation is taken into account. Therefore, this thesis concludes that actual market and simulated market are distinguishable quantitatively from various perspectives.

5.3 APPLICATION TO TRADING SYSTEMS

It is considered how to apply the indicators used in this thesis to a trading system and this thesis gives three examples. Although all of them have simple logic, the results obtained seem to be able to reach a practical level by some improving.*[23]

ENDNOTES

*[1]β A study of the top 30 sales of one month at a large system-trading software sales site showed that 22 of them specified a single target market and/or timeframe in which to operate. (researched by the author on August 25, 2023 at https://www.gogojungle.co.jp/).

*[2]β In principle, daily, weekly and monthly data were obtained from Yahoo! Finance (US), which is publicly available. However, for the data listed below, the following publicly available data were used due to the period of data availability or not being present on Yahoo! Finance (US).

USD/JPY, Crude Oil(WTI), Gold : Investing.com (US)

TOPIX : Yahoo! Finance (JPN)

For timeframes of 60-minutes or less, 5-minutes, 15-minutes, and 60-minutes timeframes were created by the author's computer program using 1-minute data for FX and CFD trading published by Axiory Global Ltd. (USD/JPY, Gold) or GMO CLICK Securities, Inc. (others). Although some markets have data prior to 30 years ago (1993), data for the recent 30 years (from July 1,1993 to June,30 2023) were used due to variations of start dates.

The number of data is shown in the table below. It is determined to be statistically sufficient, with the exception of monthly timeframe. Note that this number of data includes the overhead required for the calculation. Otherwise, for example, the calculation period would increase by 45 for 50 EMA compared to 5 EMA, and data that exceeds the predetermined period (July 1993 to June 2023) in the past direction would be included in the calculation.

Although the data used are publicly available information, the data have been compiled and processed for use in this paper, therefore the responsibility for any errors is attributable to the author.

Numbers of data

period	1993.07-2023.06 (**1999.12-2023.06)			2022.01.01-2022.12.31			
timeframes	monthly	weekly	daily	60mins	15mins	5mins	1min
S&P500	360	1,565	7,554	5,903	22,854	68,558	342,779
Nasdaq Composite*	360	1,565	7,554	5,878	22,762	68,288	341,441
Nikkei225	360	1,565	7,392	5,791	22,632	67,890	339,443
TOPIX	360	1,565	7,366	-	-	-	-
USD/JPY	360	1,565	7,821	6,214	24,854	74,537	371,187
Crude Oil(WTI)	360	1,565	7,654	5,916	23,647	70,939	354,680
Gold**	283	1,240	6,030	5,916	23,655	70,949	354,617
simulated market	One million data were generated. 7,500, 24,000, 70,000 and 350,000 consecutive arbitrary intervals were extracted from the data.						

*from 60mins to 1min : NASDAQ100

**The gold futures market is treated as a reference value due to the short acquisition period.

*[3] β©NTAA, 2002, now unlisted.

The specifications of this EXCEL file are as follows.

1) First, one arbitrary number is given, and then a random number generated by the RAND function is added to it, converted to an integer, to create a sequence of 10 numbers. The first and the last of these are the Open and Close, and the maximum and minimum are considered High and Low, creating a bar.

2) Add a random number generated by the RAND function to the previous Close to create the next Open, and repeat the operation above to create random prices one after another.

In this way, the system creates a simulated market with random price fluctuations. Some improvements made by the author are as follows;

3) To ensure that price fluctuations explicitly follow a normal distribution, the NORMINV function was applied to the values obtained by RAND function. Parameters were set to NORMINV(RAND(),0,1) so that it would be a standard normal distribution. No integer conversion was applied.

4) For simplicity, the initial value is set to 0. Therefore, the value may naturally be negative, but here the value movement was important, and the apparent positive or negative value did not affect the verification.

Note that even in the process up to 2), the price fluctuations were quite close to a normal distribution.

*[4] βAs an example, when measured the daily timeframe from January 1962 to June 2023 (a period that OHLC are recorded) using DoMA, the average required for the 20EMA to turn was 9.7 days when calculated using TP, whereas 8.3 days at Close. The same was always the case with EMAs of other calculation periods and other markets. Also, the same trend was observed for other technical indicators. Therefore, in many places in this thesis, TP is given priority in analyses.

*[5]β Focusing on the turn of moving averages is common, and there is likely precedent for similar measurements.

*[6] βThe number of consecutive bars is counted as follows. If the previous bar falls compared to the another previous Close, and the current bar rises compared to the previous Close, the current bar is set to 0. If the next bar also rises, the bar is set to 1. If the next one also rises, the count goes up to 2. If it falls, the count goes back to 0. As long as the price keeps falling and rising for each bar forward, the counts will all be 0.

*[7] βThe simulated market was measured by randomly selecting an interval of the required number of bars from the one million bars.

*[8] The number of bars per year varies slightly from market to market, so the average here is not a strict term.

*[9] The values above 2β measured at TP were slightly larger than those measured at Close, which was also the same as the simulated market.

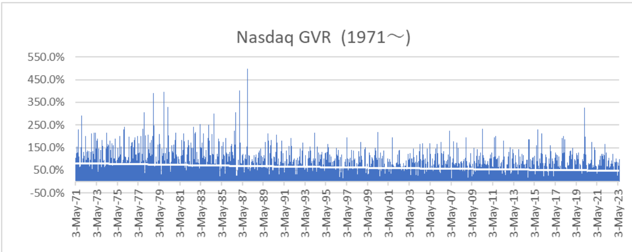
*[10]β Only Gold has data starting in 1999.

*[11] In view of the difference of GVR between at TP and at Close, it can be said that the change of TP is more moderate than that of Close, whereas the change of Close in the simulated market follows a normal distribution. The cause is presumably due to an equalization effect.

*[12]β The table below compares the S&P500, Nasdaq100 and Nikkei225 by creating 1440-minutes bars from one-minute bars of 2022.
The 1440-minutes data here is of CFD, which is continuous for almost 24 hours because the nighttime session is connected to the intraday trading. On the other hand, the daily-timeframe of stock indices that GVR shows large values of around 50 contains the prices of only the stock markets' opening hours. In the 1440-minute timeframe, normal levels of GVR values are shown. This suggests that the gap created during off-session hours would be larger for a normal daily bar, since the gap is entered directly when calculating the difference between the previous day's TP or Close and that of the current bar. On a weekly-timeframe, the impact of the gap is once a week, but on a daily-timeframe, the impact is more significant since it is five times a week. This might be one reason for the phenomenon that there appears to be little continuity between the 60-minutes and daily timeframe on the table. A similar phenomenon can be observed in other indicators.

	S&P500		NASDAQ		Nikkei225	
	GVR	Percentage of within 100	GVR	Percentage of within 100	GVR	Percentage of within 100
1440 minutes(2022)	43.6%	94.3%	40.7%	95.5%	39.6%	95.5%
Daily(2022)	50.0%	90.3%	49.6%	89.5%	60.1%	84.3%

that GVR have historically declined (white log-approximation curve in the figure below), but it cannot be said that this is certainly right due to the paucity of samples. However, it is confirmed that there has been almost no change in the average of GVR in any of the markets over the last 30 years covered in this thesis.



*14 This observation demonstrates that expressions such as, for example, “short-term trading is risky because the five-minute bar is rougher than the daily bar”, or “the stock market has milder price fluctuations than the commodity market”, are only subjective and essentially unconvincing.

*15 Here, a trend is a directional price movement accompanied by an effect of artificial bias. A directional movement can also be seen in a simulated market.

*16 βAs shown in Figure 3, the U.S. stock indices show a long-term up trend with less noise than the others throughout the 30-year observation period, but in this figure, periods such as 20EMA of daily or weekly timeframe are too small to observe. However, the results in 4.4 show that even moving averages on weekly or daily have better durability in stock indices than in the other markets.

*17 In many cases, the explanations of Bollinger Bands on the websites of securities companies and other personal sites in Japan are written this way. For example, "It is used to predict future prices based on the expectation that prices will move between the +2β (standard deviation) and -2β lines with high probability. Note that, statistically, the probability of settling between +2β and -2β is 95.45%."

(https://www.smbcnikko.co.jp/terms/japan/ho/J0054.html English translation is by the author.)

However, prices will not settle between those lines 95% of the time.

*18 ββThis calculation was done at Close because it mimics an actual trading. An example is showed below.

If the number of consecutive times = 2 in ascending;

at the Close of the bar that has a consecutive count of 2, enter the market with a buy (trend-follow) or sell (contrarian), and close the position at Close of the next bar. The price fluctuation is recorded as positive for a win and negative for a loss, and the average range of positive and negative values for the entire aggregate period is calculated. The number of wins and losses are counted, then the win/loss ratio is calculated, and then the average win price range × win ratio (A) and the average loss price range × loss ratio (B) are calculated, and finally the absolute value of (A/B) is obtained.

*19 βFor a detailed evaluation of the trading system, it should be aggregated by splitting the entire period. Furthermore, with the methods as described in Aronson's "Evidence-Based Technical Analysis" (Aronson 2009), it should be finally undergone rigorous verifications. Since trading system construction is not the main subject of this thesis, this section is limited to the part of the verification process that corresponds to the "preliminary verification" proposed by Pardo (Pardo 2008, pp 245-270).

*20 Listing below are the spread and the number of lots used in section 4.7.

market	spread	currency	lot
S&P500	0.3	USD	1
Nasdaq	0.6	USD	1
Nikkei225	3.0	JPY	10
TOPIX	0.4	JPY	100
USDJPY	0.002	JPY	1000
WTI	0.03	USD	10
GOLD	0.4	USD	1

・The average spread of CFD and FX providers in Japan.
・The lot is used for basket trades.

*21 βThe daily timeframe was used. The maximum trade period was set at 3 days, since a large reversal of the arbitrage trading is dangerous. Since the two markets differ greatly in value, the Nasdaq/S&P500 multiple was measured daily and the number of lots in that ratio was used. However, when closing the position, the same lot was used as when new. A multiple of 2.3 means 2.3 S&P500 for every 1.0 Nasdaq. Since the multiplier is to the first decimal place, the actual number would be 23 and 10. The win/loss amount also takes into account the spread.

*22 Because of the huge losses involved in market abruptness, setting a loss cut to a generally acceptable value improved performance, but it was not reflected in the Table 20 because it would be an extra factor in the comparison between markets.

*23 As for the application to trading systems, it has not yet been tested, but could include the following.

βWhile the DoMA at EMA(50) is in duration (but shorter than the average duration of that market and while the trend is young), enter when the price goes backwards and RSI shows a value corresponding to above 2β.

βInstead of going against the Bollinger Band as soon as it crosses 2β line, entering against it when the percentage of above-2β exceeds the standard value in the simulated market (approx. 13% at TP).

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Chicken and Egg: Should You Use the VIX to Time the SPX, or Use the SPX to Time the VIX?

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Abstract

This article presents an exploration into the reciprocal predictive relationships between the S&P 500 Index (SPX) and the CBOE Volatility Index (VIX), with a particular focus on deriving actionable insights for market timing strategies. This comprehensive study challenges the prevailing market wisdom by positing that SPX action offers a more reliable basis for forecasting VIX movement than VIX action does in forecasting SPX movement.

The introduction sets the stage by questioning the traditional reliance on the VIX as a market timing tool, suggesting instead that SPX movements may offer valuable insights into future VIX trends. Numerous works are cited sampling publicly available research. Most past research has utilized VIX as an indicator for SPX. The study probes deeper to understand the extent to which one index can predict the movements of the other.

The paper then explains the history and construction of the VIX. It shows how the VIX has moved during all major market selloffs since 1990, which is as far back as our VIX data is available.

The next section is a discussion of implied and historical volatility (HV). It begins with a dialogue of the "Rule of 16", and what different VIX readings actually represent. This section lays the groundwork for better understanding the interaction between SPX and VIX, and why the movements of SPX influence option traders and their willingness to pay more for portfolio protection. As it turns out, options traders are more likely to be reactionary than anticipatory.

At this point, the paper examines VIX versus SPX readings as short-term market indicators. Two types of studies are done here. One uses short-term RSI readings of 2, 3, and 4 days. The other looks at short-term high and low readings, from 5 to 25 days in length. Readings are calculated on SPX and also on VIX. Data is then examined which shows the SPX readings tend to be more useful in anticipating SPX movement than VIX readings are. The data is sliced several ways, and the answer consistently suggests SPX readings offer more robust edges for trading.

There is then a discussion of VIX-based securities and why traders and investment managers may want to consider them in a portfolio. One of the primary reasons demonstrated is that they have shown an incredible downside persistency. While counter moves can be sharp during market crises, VIX-based securities (futures and exchange-traded products) have typically gone substantially shorter periods between making new all-time lows than SPX has in making new all-time highs. The Great Financial Crisis of 2007-2008 along with the 2022 bear market are discussed in detail. Analysis implies that a well-constructed short-VIX strategy should have an edge over a long-SPX strategy when looking to avoid lengthy periods of drawdown.

With this in mind, studies are shown that are constructed in a similar manner to those that examined SPX movements. The paper again utilizes short-term RSI readings and short-term high-low readings of both SPX and VIX. This time it examines their value as indicators for VIX futures movements. Again it is found that SPX readings tend to act as a superior indicator. Data here is also broken down to examine behavioral differences when SPX is in a long-term uptrend (above its 200ma) versus a long-term downtrend (below its 200ma).

While the data tables show strong evidence that SPX readings could be used effectively to find favorable opportunities for shorting VIX futures, the final section takes it a bit further. To show the consistency that the edge has exhibited over time, a simple model is built using some of the concepts and indicators previously examined. The model makes it clear that the research is capable of serving as a core component in winning strategies that could be developed for investors.

Final analysis declares that SPX indicators, particularly overbought/oversold measures, possess a markedly higher predictive value for VIX movements than previously recognized.

The paper challenges conventional wisdom and presents a compelling case for the predictive superiority of SPX over VIX in the context of trading both SPX and VIX-based securities. This sets the stage for further research while providing traders and investment managers tools to realize untapped potential in leveraging SPX action for more informed and effective trading decisions in the volatility space.

Introduction

Do bigger chickens produce bigger eggs? Do bigger eggs lead to bigger chickens? We might not know whether the chicken or the egg came first, but we can probably learn the answer to the above. When looking at the market, we know that the S&P 500 (SPX) came before the CBOE Volatility Index (VIX). But which does a better job of predicting the other? And more importantly, where do the biggest trading edges lie?

There has been ample research published over the years that examined CBOE Volatility Index (VIX) action, and how VIX readings might be used to predict S&P 500 movement. In their 2004 book, "How Markets Really Work", Larry Connors and Conor Sen showed how short-term overbought and oversold VIX readings were a useful indicator for short-term SPX movement. Connors has since published additional research along these lines.

In 2018, Fassas and Hourvouliades published "VIX Futures As A Market Timing Indicator" which examined VIX futures term structure for anticipating forward S&P 500 returns.

In his 2020 NAAIM Founders Award paper, "Actively Using Passive Sectors to Generate Alpha Using the VIX" Michael Gayed used the VIX in timing allocation adjustments between sectors.

Studies have also been published that examine short volatility strategies, such as "VIX Index Strategies, Shorting volatility as a portfolio enhancing strategy", by Dondoni, Montagna, and Maggi (2018). There they identified the long-term tendency of VIX futures to decline and used the VIX futures term structure to aid in timing short volatility positions.

A primary use of VIX among researchers and market participants has been as an indicator for timing the SPX and other markets. Years of trading experience and research has taught me that more value may be found in doing the converse. Therefore, I will examine approaches that use SPX action as an indicator for trading VIX-based securities, primarily VIX futures. Before getting to that, I will discuss the VIX itself, what its readings represent, and historical tendencies of the VIX. I'll then examine whether VIX readings are any more predictive of SPX movement than simply using SPX readings. I'll examine VIX futures (VX) movement, the use of SPX indicators as a VX trading filter, and finally, a simple model that incorporates some of the research.

VIX Overview

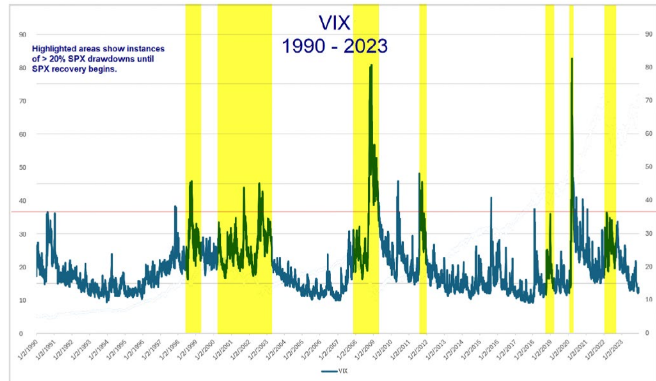
The VIX was created by the Chicago Board of Options Exchange (CBOE). It measures 30-day S&P 500 volatility expectations based on SPX option prices. To get the 30-day average, it considers option prices in the 23 to 37-day range. The VIX will generally deliver "high" readings in volatile and uncertain conditions. "Low" readings are often found during quiet market environments. From 1990 – 2023 the range of closing VIX prices was between 9.14 and 82.69.

The VIX is not tradeable, but there are tradeable instruments based on the VIX. VIX futures were the first instrument to be based on the VIX index. They began trading in 2004, though volume was quite muted in the early years. In 2006 VIX options were introduced. Then in 2009, we saw the first VIX-based ETFs arrive. Interest in using VIX-based instruments has grown substantially over the years. For some they are used as a hedging instrument, and for others they are traded as a separate strategy.

The reason VIX products became a popular hedge is that the VIX will often trade inversely to the SPX. The basic reason for this is that falling markets will generate fear. The desire for protection increases and traders are generally more willing to pay a larger premium for options to protect their portfolios. When SPX is on the rise, investors feel good. There is less demand for portfolio protection. People are not willing to pay as much for options in a rising market as in a falling market. So the reduced options premium is reflected in the lower VIX reading.

Below is a long-term chart of daily VIX closing prices. Though SPX is not shown on the chart, yellow highlighted sections are times where the SPX experienced a 20% drawdown or more.

Figure 1



VIX spikes occurred during all of the tumultuous S&P 500 drawdowns, including the 1998 Long-Term Capital blowup, the 2000-2003 tech bear, the 2008 Great Financial Crisis, the 2020 COVID Crash, and others. But as you can see, the VIX tended to revert to more normal levels quite quickly, even when the S&P 500 took an extended amount of time to recover its losses. Quicker recovery time is a key concept. And it not only applies to the VIX, but as I will show later, it also applies to tradeable VIX-based products.

I will also share another observation here. The 2022 high level is shown by the red line. Along with the December 2018 bear, this is about as low a reading as we have seen during a bear market. That surprised some people, but it shouldn't have. There was nothing particularly scary about the 2022 bear market. It was primarily caused by a rise in interest rates. Rising interest rates are not nearly as scary as a worldwide financial crisis or a 100-year pandemic. Further, realized volatility never spiked in 2022 like we saw in other periods. So with actual price movement not extreme and the "big scare" being rising interest rates, why would people expect the VIX to reach the kind of levels that were seen in some other bear markets? They shouldn't.

Implied & Historical Volatility

I think part of the problem with people misunderstanding where the VIX "should" be is that they do not understand implied volatility, and they especially don't understand what the VIX readings represent. Implied volatility is an estimate of daily variations in price. The VIX measures options that are priced on the S&P 500. It is the implied volatility of those SPX options that average 30 days to maturity. But it is not a "daily" number. It is "annualized". This leads us to the "Rule of 16".

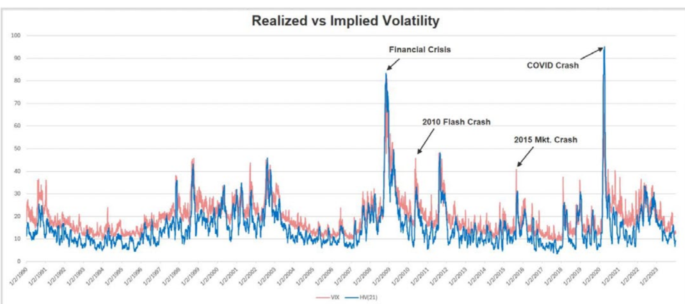
To convert an annual implied volatility number into a daily number you need to take the square root of the number of days. There are approximately 252 trading days in a year. The square root of 252 is 15.875 (about 16). So a VIX reading of 16 represents daily implied volatility of about 1% over the next 30 days. (More specifically, it suggests that 68.2% of days will see price changes of less than 1%, and 31.8% of the time the SPX could change by more than 1%.) A VIX of 32 implies 2% moves are likely, 48 would anticipate numerous 3% moves, and for the VIX to be at 80, implied volatility on SPX options would be pricing in 5% daily moves.

If you have observed the S&P 500 for very long, you will realize that price changes of 5%, 4%, 3%, or even 2% in one day are quite rare. Going through an extended period of time where daily moves are averaging even 2% is highly unusual. So it is understandable that a VIX of even 30 or 40 is not common.

When price action in the S&P 500 becomes more volatile, the VIX therefore naturally spikes. And when S&P 500 volatility begins to quiet down, it is unlikely that the VIX will remain elevated.

When considering what volatility expectations might be over the next month, the easiest way to estimate this would be to look at what volatility has been over the last month. One month forward is rounded to 30 days for the VIX. One month backward can be rounded to 21 (trading) days for historical volatility (HV). The chart below shows VIX readings in red and 21-day HV of SPX in blue, going back to the inception of the VIX in 1990.

Figure 2



A few notes:

- Perhaps the most apparent observation I could make about the chart is that the lines tend to move together. They rise and fall at about the same time, never getting too far off track.
- The red line (VIX) is typically above the blue (HV). So estimations of implied volatility are generally a little higher than what has been seen from a volatility standpoint in the recent past. This makes sense. The next 30 days' action is unknown, and options sellers will typically be able to demand a premium for taking on unknown risks.
- There are a couple of instances marked on the chart that HV reached similar levels to the 2022 highs, but VIX spiked quite a bit higher. They were in 2010 and 2015. Important to note about both these instances is that they were quick market shocks. HV transitioned from a low level to up over 30 very quickly both times. In other words, there was a brief but powerful market shock that VIX quickly adjusted to, and this caused it to elevate more substantially above HV.
- The 2022 high levels in HV were achieved through a more gradual rise. Options traders had more time to adjust to increased volatility, and so VIX remained more in line with HV as compared to the 2010 and 2015 instances.

So VIX is a measure of implied volatility for S&P 500 options. It is not related to actual, historical volatility, but the two are highly correlated.

I mentioned the VIX often trades inversely to the SPX. Let's look at a chart so you can see what I mean by this.

Figure 3

This chart is from 2022. You can see here how moves up in SPX generally coincide with moves down in the VIX, and vice versa. Because VIX direction is often inverted versus SPX, the tendency over the years has been to use VIX as an indicator for SPX. Let's take a quantitative look to evaluate whether VIX is likely a useful indicator for SPX movement. I will look at it from both a long-term and a short-term perspective.

VIX vs SPX Readings as a Long-Term Market Filter

I do not recall reading any research in the past that used VIX as an effective long-term indicator. Of course SPX long-term trend measures and long-term moving averages can be used to potentially sidestep portions of bear markets, reduce drawdown, and in many cases increase long-term returns.

So I took 3 simple S&P 500 long-term trend filters to see how utilizing them might compare to a Buy & Hold approach with the S&P 500. The 3 trend filters I chose were:

1) *Whether the SPX closed higher than it closed 1 year ago (252 trading days)*
2) *Whether the SPX closed above its 200-day moving average.*
3) *Whether the 50-day moving average closed above the 200-day moving average (also known as the Golden Cross formation).*

The test assumed that when the trend filter suggested an uptrend that SPX was entered. When SPX was not in an uptrend, then the portfolio would go to cash, and earn interest at the overnight Fed Funds rate.

Lastly, I took the same indicators and applied them to the VIX. Since the VIX typically mirrors the SPX, I reversed them. So the portfolio would go long if:

1) *The VIX closed below where it did 1 year ago.*
2) *The VIX closed below its 200-day moving average.*
3) *The 50-day moving average of the VIX closed below the 200-day moving average.*

Results using these six filters, along with "Buy & Hold" returns can be found in the table below.

Figure 4

SPX Performance Based on Long-Term Filters Using SPX or VIX.
$10,000 starting account. 1992 - 2023.

Long-Term Trend Id	# Trades	Net Profit	CAGR	Exposure %	Max. Sys % Drawdown	CAR/MDD
Buy & Hold	1	$104,359.73	7.91	100	-56.78	0.14
SPX Up Year	62	$106,382.64	7.97	78.73	-25.04	0.32
SPX > 200-day MA	114	$65,731.04	6.53	74.99	-22.1	0.3
SPX Golden Cross	15	$121,113.70	8.37	75.44	-33.92	0.25
VIX Down Year	292	$28,767.73	4.32	51.66	-38.65	0.11
VIX Below 200ma	320	$36,145.84	4.89	60.8	-36.94	0.13
VIX 50ma < 200ma	35	$41,683.38	5.26	60.48	-47.8	0.11

We see here that using SPX trend filters was generally successful. Two of the three SPX filters outperformed Buy & Hold total returns. They all reduced drawdowns. And the Compound Annual Return / Max Drawdown (CAR/MDD) stats were improved using all 3 filters.

But the long-term VIX filters did not seem to help anything. They all showed lower net profits, and the CAR/MDD was worse than Buy & Hold in every case. It appears long-term measures of the VIX are not helpful as a filter for SPX.

VIX vs SPX Readings as a Short-Term Market Indicator

Most publicly available VIX-related research has focused on using VIX measures to anticipate SPX action. However, my research has not found VIX action to be any more predictive of SPX movement than simply using SPX action.

I'll use two different measures of overbought/oversold to demonstrate. The first indicator to consider is Wilder's RSI. Short-term measures of RSI are used here for a couple of reasons: 1) I have found that shorter-term RSIs tend to indicate short-term action better than longer-term RSIs. 2) Short-term RSIs tend to offer more evenly distributed delineation. For instance, a 14-period RSI will see most readings fall between 30 and 70. But a 2-period RSI will have plenty of instances below 30 and above 70. This makes for neater delineation.

The first series of tests utilize RSI(2). All of these tests are run from 2007 – 2023. This was done to include the Great Financial Crisis, and also to measure a period where both VIX futures and options were available. 2007 is the first full year where that was the case.

This first results table shows next-day returns in SPX when its RSI(2) closed in 5 different quintiles. It also incorporates a long-term filter (SPX 200-day moving average) for the bottom 10 rows.

Figure 5

Next Day SPX Performance Based on RSI(2) of SPX.
2007 - 2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	RSI <= 20	2	822	57.66	0.18	1.41
0 Long-Term Filter	RSI > 20 and <= 40	2	635	55.43	0.06	1.14
0 Long-Term Filter	RSI > 40 and <= 60	2	603	52.4	-0.04	0.93
0 Long-Term Filter	RSI > 60 and <= 80	2	851	55.23	0.03	1.08
0 Long-Term Filter	RSI > 80 and <= 100	2	1367	51.5	-0.03	0.91
Above 200-day MA	RSI <= 20	2	500	59.4	0.1	1.28
Above 200-day MA	RSI > 20 and <= 40	2	453	55.41	0.04	1.12
Above 200-day MA	RSI > 40 and <= 60	2	443	52.6	0.01	1.04
Above 200-day MA	RSI > 60 and <= 80	2	677	55.39	0.02	1.09
Above 200-day MA	RSI > 80 and <= 100	2	1129	52.35	0.01	1.03
Below 200-day MA	RSI <= 20	2	322	54.97	0.32	1.53
Below 200-day MA	RSI > 20 and <= 40	2	182	55.49	0.12	1.16
Below 200-day MA	RSI > 40 and <= 60	2	160	51.88	-0.17	0.82
Below 200-day MA	RSI > 60 and <= 80	2	174	54.6	0.05	1.07
Below 200-day MA	RSI > 80 and <= 100	2	238	47.48	-0.19	0.71

Results here show some interesting delineation, and are suggestive of an edge that would be worthwhile to consider. Low RSIs (especially below 20) provide the strongest numbers.

Such oversold conditions led to net positive next-day returns. Meanwhile, overbought conditions (RSI > 80) showed negative returns. This was especially true during a long-term downtrends (bottom row). During long-term uptrends (above the 200ma), RSI>80 results were actually slightly positive. Also notable: 1) Some people may not be familiar with “Profit Factor”. It is Gross Gains / Gross Losses. So a profit factor above 1 means that the strategy is profitable. A reading below 1 means the strategy has lost money over time. Profit factor can be a helpful measure of reward/risk when evaluating strategies. 2) Results when SPX is in a downtrend tend to be more extreme — both bullish and bearish. It may seem odd that average gains are much higher during “oversold in downtrends” than they are during “oversold in uptrends”, but volatility tends to be higher during downtrends. When volatility is higher it makes moves more sizable. Hence the more extreme numbers during downtrends. This will be evident in results throughout the paper. 3) The theme of oversold providing an upside edge and overbought suggesting a neutral or bearish market condition is something you will continue to see throughout the research as well.

So now let’s use the same RSI(2) indicator and apply it to the VIX to see if that might provide an edge for trading SPX.

Figure 6

Next Day SPX Performance Based on RSI(2) of VIX.
2007 - 2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	0 ST Filter	2	4278	54.79	0.04%	1.11
0 Long-Term Filter	RSI of VIX <= 20	2	1108	55.51	0.05%	1.14
0 Long-Term Filter	RSI of VIX > 20 and <= 40	2	914	54.81	0.01%	1.03
0 Long-Term Filter	RSI of VIX > 40 and <= 60	2	740	53.65	-0.02%	0.95
0 Long-Term Filter	RSI of VIX > 60 and <= 80	2	686	55.69	0.06%	1.14
0 Long-Term Filter	RSI of VIX > 80 and <= 100	2	830	54.1	0.13%	1.3
Above 200-day MA	0 ST Filter	2	3202	55.47	0.04%	1.13
Above 200-day MA	RSI of VIX <= 20	2	834	56.35	0.04%	1.17
Above 200-day MA	RSI of VIX > 20 and <= 40	2	708	55.93	0.04%	1.15
Above 200-day MA	RSI of VIX > 40 and <= 60	2	551	52.99	0.00%	0.99
Above 200-day MA	RSI of VIX > 60 and <= 80	2	499	58.32	0.09%	1.34
Above 200-day MA	RSI of VIX > 80 and <= 100	2	610	53.61	0.02%	1.07
Below 200-day MA	0 ST Filter	2	1076	52.79	0.06%	1.09
Below 200-day MA	RSI of VIX <= 20	2	274	52.92	0.07%	1.11
Below 200-day MA	RSI of VIX > 20 and <= 40	2	206	50.97	-0.09%	0.89
Below 200-day MA	RSI of VIX > 40 and <= 60	2	189	55.56	-0.08%	0.9
Below 200-day MA	RSI of VIX > 60 and <= 80	2	187	48.66	-0.03%	0.96
Below 200-day MA	RSI of VIX > 80 and <= 100	2	220	55.45	0.41%	1.66

Some of the same themes play out here, but not as impressively. An overbought VIX (RSI > 80, 0 Long-Term Filter, 6th row down) suggests the SPX may be primed to bounce. But an oversold VIX (RSI <= 20, 2nd row down) shows numbers that are very close to the numbers shown when there is no filter at all (top row). So while an overbought VIX could provide an edge, an oversold VIX does not appear to generate a quantifiable edge.

Let’s next look at RSI(3) for SPX and VIX, in order to assess whether the themes play out here as well.

Figure 7

Next Day SPX Performance Based on RSI(3) of SPX.
2007 - 2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	RSI <= 20	3	457	59.52	0.29	1.6
0 Long-Term Filter	RSI > 20 and <= 40	3	782	54.22	0.04	1.09
0 Long-Term Filter	RSI > 60 and <= 80	3	1161	53.83	0.03	1.08
0 Long-Term Filter	RSI > 40 and <= 60	3	944	54.66	-0.02	0.96
0 Long-Term Filter	RSI > 80 and <= 100	3	934	51.28	-0.02	0.92
Above 200-day MA	RSI <= 20	3	248	62.5	0.2	1.58
Above 200-day MA	RSI > 60 and <= 80	3	917	54.31	0.02	1.08
Above 200-day MA	RSI > 40 and <= 60	3	683	54.76	0.02	1.06
Above 200-day MA	RSI > 20 and <= 40	3	531	54.8	0.01	1.04
Above 200-day MA	RSI > 80 and <= 100	3	823	52.13	0.01	1.03
Below 200-day MA	RSI <= 20	3	209	55.98	0.39	1.61
Below 200-day MA	RSI > 20 and <= 40	3	251	52.99	0.11	1.15
Below 200-day MA	RSI > 60 and <= 80	3	244	52.05	0.05	1.08
Below 200-day MA	RSI > 40 and <= 60	3	261	54.41	-0.13	0.84
Below 200-day MA	RSI > 80 and <= 100	3	111	45.05	-0.22	0.62

Once again, an RSI of SPX under 20 suggests a short-term bullish edge, and an RSI over 80 suggests a neutral (during uptrends) or bearish (during downtrends) edge.

Next let's apply RSI(3)of VIX as a delineator.

Figure 8

Next Day SPX Performance Based on RSI(3) of VIX.
2007 - 2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	RSI of VIX <= 20	3	569	54.31	0.02%	1.05
0 Long-Term Filter	RSI of VIX > 20 and <= 40	3	1292	56.81	0.07%	1.22
0 Long-Term Filter	RSI of VIX > 40 and <= 60	3	1121	51.92	-0.04%	0.9
0 Long-Term Filter	RSI of VIX > 60 and <= 80	3	836	56.34	0.09%	1.2
0 Long-Term Filter	RSI of VIX > 80 and <= 100	3	460	53.91	0.15%	1.34
Above 200-day MA	RSI of VIX <= 20	3	418	55.74	0.05%	1.2
Above 200-day MA	RSI of VIX > 20 and <= 40	3	1014	56.9	0.05%	1.2
Above 200-day MA	RSI of VIX > 40 and <= 60	3	841	52.44	-0.02%	0.95
Above 200-day MA	RSI of VIX > 60 and <= 80	3	590	57.8	0.09%	1.33
Above 200-day MA	RSI of VIX > 80 and <= 100	3	339	54.28	0.04%	1.1
Below 200-day MA	RSI of VIX <= 20	3	151	50.33	-0.07%	0.88
Below 200-day MA	RSI of VIX > 20 and <= 40	3	278	56.47	0.15%	1.25
Below 200-day MA	RSI of VIX > 40 and <= 60	3	280	50.36	-0.13%	0.85
Below 200-day MA	RSI of VIX > 60 and <= 80	3	246	52.85	0.07%	1.09
Below 200-day MA	RSI of VIX > 80 and <= 100	3	121	52.89	0.47%	1.74

Here again, an overbought VIX suggests an upside edge for SPX, but an oversold VIX does not appear greatly predictive. An oversold VIX when SPX is in a downtrend does show slightly bearish results, but not nearly to the extent that an overbought RSI(3) of SPX does.

Finally...RSI(4). First, SPX:

Figure 9

Next Day SPX Performance Based on RSI(4) of SPX.
2007 - 2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	RSI <= 20	4	285	60	0.31	1.63
0 Long-Term Filter	RSI > 20 and <= 40	4	820	54.39	0.05	1.1
0 Long-Term Filter	RSI > 40 and <= 60	4	1145	54.24	0.02	1.05
0 Long-Term Filter	RSI > 60 and <= 80	4	1405	54.59	0.01	1.03
0 Long-Term Filter	RSI > 80 and <= 100	4	623	49.92	-0.02	0.91
Above 200-day MA	RSI <= 20	4	140	62.14	0.23	1.61
Above 200-day MA	RSI > 20 and <= 40	4	520	56.92	0.04	1.1
Above 200-day MA	RSI > 60 and <= 80	4	1142	55.25	0.02	1.09
Above 200-day MA	RSI > 40 and <= 60	4	821	53.59	0.02	1.06
Above 200-day MA	RSI > 80 and <= 100	4	579	50.6	0.01	1.03
Below 200-day MA	RSI <= 20	4	145	57.93	0.39	1.64
Below 200-day MA	RSI > 20 and <= 40	4	300	50	0.08	1.1
Below 200-day MA	RSI > 40 and <= 60	4	324	55.86	0.03	1.04
Below 200-day MA	RSI > 60 and <= 80	4	263	51.71	-0.04	0.93
Below 200-day MA	RSI > 80 and <= 100	4	44	40.91	-0.38	0.37

Again low RSI readings suggest an upside edge and high RSI readings suggest a next-day downside edge. Results here are a bit more extreme. Part of the reason for this is that it takes larger moves to get extreme readings with a 4-period RSI than a 2-period RSI. That is why you also see the lower number of instances where RSI was below 20 or above 80.

And VIX...

Figure 10

Next Day SPX Performance Based on RSI(4) of VIX.
2007 - 2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	RSI of VIX <= 20	4	253	50.99	-0.07%	0.8
0 Long-Term Filter	RSI of VIX > 20 and <= 40	4	1443	55.99	0.06%	1.19
0 Long-Term Filter	RSI of VIX > 40 and <= 60	4	1435	53.94	0.01%	1.02
0 Long-Term Filter	RSI of VIX > 60 and <= 80	4	862	55.22	0.06%	1.13
0 Long-Term Filter	RSI of VIX > 80 and <= 100	4	285	55.09	0.23%	1.51
Above 200-day MA	RSI of VIX <= 20	4	180	52.78	-0.02%	0.92
Above 200-day MA	RSI of VIX > 20 and <= 40	4	1128	56.21	0.04%	1.19
Above 200-day MA	RSI of VIX > 40 and <= 60	4	1075	54.79	0.02%	1.07
Above 200-day MA	RSI of VIX > 60 and <= 80	4	607	56.18	0.06%	1.18
Above 200-day MA	RSI of VIX > 80 and <= 100	4	212	55.19	0.08%	1.22
Below 200-day MA	RSI of VIX <= 20	4	73	46.58	-0.19%	0.68
Below 200-day MA	RSI of VIX > 20 and <= 40	4	315	55.24	0.10%	1.18
Below 200-day MA	RSI of VIX > 40 and <= 60	4	360	51.39	-0.04%	0.95
Below 200-day MA	RSI of VIX > 60 and <= 80	4	255	52.94	0.06%	1.08
Below 200-day MA	RSI of VIX > 80 and <= 100	4	73	54.79	0.65%	1.98

No surprise here. An overbought VIX suggests an upside edge, but not as strongly as an oversold SPX. Interestingly, the number of instances where VIX registered an RSI(4) reading greater than 80 was the same number of instances that SPX registered an RSI(4) less than 20. It was 285 instances. RSI of SPX showed a higher % Winners (60% vs 55%), larger average move (0.31% vs 0.23%), and a better profit factor (1.63 vs 1.51). Using RSI to measure overbought/oversold VIX, could identify opportune times to take short-term trades to the long side. But simply using the same measures on SPX appears to provide a more reliable edge.

Of course RSI is just one measure of overbought/oversold. Next let's look at an even simpler one. Here we are going to examine whether SPX (and later VIX) closed at a multi-day high, a multi-day low, or somewhere in between. I'll also delineate "in between" into two buckets using a moving average. So the 4 quadrants are 1) at an X-day low, 2) below the X-day moving average (but above an X-day low), 3) above the X-day moving average (but below an X-day high), and 4) at an X-day high.

The table below uses 10 for X.

Figure 11

Next Day SPX Performance Filtered by High-Low-Upper-Lower Quandrant 10-Day Close
and 200ma Filter. 2007 - 2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	1 - Lowest Close	10	554	58.3	0.2	1.4
0 Long-Term Filter	2 - Below Avg Close	10	1078	54.55	0.02	1.05
0 Long-Term Filter	3 - Above Avg Close	10	1532	54.83	0.04	1.11
0 Long-Term Filter	4 - Highest Close	10	1114	50.72	-0.04	0.86

After seeing the RSI results, these results are no surprise. Oversold suggests an upside edge, and overbought a mild downside edge. Breaking it out by the 200ma also tells a similar story.

Figure 12

Next Day SPX Performance Filtered by High-Low-Upper-Lower Quandrant 10-Day Close
and 200ma Filter. 2007 - 2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
Above 200-day MA	1 - Lowest Close	10	317	60.57	0.12	1.32
Above 200-day MA	2 - Below Avg Close	10	712	55.34	0.03	1.08
Above 200-day MA	3 - Above Avg Close	10	1216	55.02	0.03	1.1
Above 200-day MA	4 - Highest Close	10	957	51.41	0	1.02
Below 200-day MA	1 - Lowest Close	10	237	55.27	0.31	1.45
Below 200-day MA	2 - Below Avg Close	10	366	53.01	0.01	1.02
Below 200-day MA	3 - Above Avg Close	10	316	54.11	0.09	1.14
Below 200-day MA	4 - Highest Close	10	157	46.5	-0.28	0.56

Closing at a low suggests an upside edge in either case. But a low close below the 200ma shows greater potential gains, while a low close above the 200ma shows more reliable gains. Again, this is similar to what we saw using RSI.

Next is a similar breakdown, but using VIX readings as the indicator, rather than SPX readings.

Figure 13

Next Day SPX Performance Filtered by **VIX** High-Low-Upper-Lower Quandrant 10-Day Close. 2007 - 2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	0 Filter - All Days	10	4278	54.14	0.04	1.09
0 Long-Term Filter	1-Highest VIX Close	10	586	55.8	0.18	1.45
0 Long-Term Filter	2-Above Avg VIX Close	10	1298	53.62	-0.02	0.97
0 Long-Term Filter	3-Below Avg VIX Close	10	1549	54.36	0.02	1.07
0 Long-Term Filter	4-Lowest VIX Close	10	845	53.37	0.04	1.14

Here we see a high VIX suggests an upside edge for SPX, while a low VIX does not appear to suggest any edge. Comparing the 10-day low SPX close to the 10-day high VIX close you'll note that the number of instances is similar, but the low-SPX setup shows a higher win rate and a higher Avg % Profit/Loss. Here is the 200ma breakout like we just did with SPX:

Figure 14

Next Day SPX Performance Filtered by **VIX** High-Low-Upper-Lower Quandrant 10-Day Close and 200ma Filter. 2007 - 2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
SPX Above 200ma	1-Highest VIX Close	10	425	54.59	0.08	1.24
SPX Above 200ma	2-Above Avg VIX Close	10	940	55	0.02	1.07
SPX Above 200ma	3-Below Avg VIX Close	10	1208	53.97	0.00	0.99
SPX Above 200ma	4-Lowest VIX Close	10	629	55.01	0.07	1.32
SPX Below 200ma	1-Highest VIX Close	10	161	59.01	0.45	1.74
SPX Below 200ma	2-Above Avg VIX Close	10	358	50	-0.12	0.86
SPX Below 200ma	3-Below Avg VIX Close	10	341	55.72	0.11	1.18
SPX Below 200ma	4-Lowest VIX Close	10	216	48.61	-0.03	0.96

Again below the 200ma shows more extreme readings. I will note that a "lowest" VIX reading when SPX is below the 200ma does show a negative forward return for SPX, but not nearly as negative as a "highest" SPX reading showed (-0.03% vs -0.28% average loss).

Lest there is concern that the 10-day period was cherry-picked, below is performance for "Lowest" and "Highest" closes for 5, 10, 15, 20, and 25 days. First for SPX, then for VIX.

Figure 15 & 16

Next Day SPX Performance Filtered for Times SPX Closed at an X-Day Low or High. 2007 - 2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	1 - Lowest Close	5	929	56.84	0.14	1.31
0 Long-Term Filter	1 - Lowest Close	10	554	58.3	0.2	1.4
0 Long-Term Filter	1 - Lowest Close	15	430	56.98	0.2	1.39
0 Long-Term Filter	1 - Lowest Close	20	356	56.46	0.23	1.42
0 Long-Term Filter	1 - Lowest Close	25	299	56.52	0.27	1.45
0 Long-Term Filter	4 - Highest Close	5	1442	51.66	-0.02	0.95
0 Long-Term Filter	4 - Highest Close	10	1114	50.72	-0.04	0.86
0 Long-Term Filter	4 - Highest Close	15	993	50.35	-0.02	0.9
0 Long-Term Filter	4 - Highest Close	20	904	50.66	-0.02	0.92
0 Long-Term Filter	4 - Highest Close	25	852	51.06	-0.01	0.95

Next Day SPX Performance Filtered for Times VIX Closed at an X-Day Low or High. 2007 - 2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
0 Long-Term Filter	1-Highest VIX Close	5	978	55.62	0.15	1.39
0 Long-Term Filter	1-Highest VIX Close	10	586	55.8	0.18	1.45
0 Long-Term Filter	1-Highest VIX Close	15	445	55.06	0.16	1.35
0 Long-Term Filter	1-Highest VIX Close	20	348	55.75	0.22	1.46
0 Long-Term Filter	1-Highest VIX Close	25	293	54.61	0.22	1.42
0 Long-Term Filter	4-Lowest VIX Close	5	1289	53.84	0.04	1.11
0 Long-Term Filter	4-Lowest VIX Close	10	845	53.37	0.04	1.14
0 Long-Term Filter	4-Lowest VIX Close	15	668	52.54	0.03	1.11
0 Long-Term Filter	4-Lowest VIX Close	20	560	51.61	0.02	1.08
0 Long-Term Filter	4-Lowest VIX Close	25	505	51.88	0.01	1.04

The lessons are the same no matter the timeframe. 1) Oversold SPX and overbought VIX both suggest an upside edge. The edge provided by SPX appears to be stronger. 2) Overbought SPX suggests a downside edge, while oversold VIX is more neutral.

You may find it curious that the downside edge for overbought SPX does not appear to increase when looking at more extreme readings (a 25-day high vs a 5-day high). This is because the 20 and 25-day high readings are so much less common below the 200ma where the edge primarily exists. You can see this in the table below that contains the 200ma breakdown.

Figure 17

Next Day SPX Performance Filtered for Times SPX Closed at an X-Day Low or High.
200ma Filter also Applied. 2007 - 2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg % Profit/Loss	Profit Factor
Above 200-day MA	1 - Lowest Close	5	592	57.26	0.06	1.17
Above 200-day MA	1 - Lowest Close	10	317	60.57	0.12	1.32
Above 200-day MA	1 - Lowest Close	15	223	59.64	0.12	1.3
Above 200-day MA	1 - Lowest Close	20	167	59.28	0.11	1.3
Above 200-day MA	1 - Lowest Close	25	121	58.68	0.12	1.29
Above 200-day MA	4 - Highest Close	5	1177	52	0	1.02
Above 200-day MA	4 - Highest Close	10	957	51.41	0	1.02
Above 200-day MA	4 - Highest Close	15	872	51.26	0.01	1.07
Above 200-day MA	4 - Highest Close	20	809	51.42	0.02	1.09
Above 200-day MA	4 - Highest Close	25	775	51.87	0.02	1.11
Below 200-day MA	1 - Lowest Close	5	337	56.08	0.29	1.45
Below 200-day MA	1 - Lowest Close	10	237	55.27	0.31	1.45
Below 200-day MA	1 - Lowest Close	15	207	54.11	0.3	1.44
Below 200-day MA	1 - Lowest Close	20	189	53.97	0.33	1.47
Below 200-day MA	1 - Lowest Close	25	178	55.06	0.37	1.5
Below 200-day MA	4 - Highest Close	5	265	50.19	-0.11	0.83
Below 200-day MA	4 - Highest Close	10	157	46.5	-0.28	0.56
Below 200-day MA	4 - Highest Close	15	121	43.8	-0.3	0.51
Below 200-day MA	4 - Highest Close	20	95	44.21	-0.31	0.51
Below 200-day MA	4 - Highest Close	25	77	42.86	-0.32	0.46

Note the downside edge continues to increase as you make higher-level highs below the 200ma (bottom 5 rows). But the instances shrink enough that the total impact is dulled when lumped together with instances above the 200ma.

Whether we use short-term RSI readings or whether we simply look at short to intermediate-term highs and lows to gauge overbought/oversold, the message appears to be the same.

- Oversold SPX readings suggest a next-day upside edge.
- The edge is more reliable above the 200ma, but more powerful below it.
- An overbought VIX provides a similar edge, but the overbought VIX stats are not as impressive.
- Overbought SPX readings suggest a downside edge, particularly when SPX is in a long-term downtrend (below its 200ma).
- Oversold VIX readings don't show much of a downside edge. If it appears at all, it is much less pronounced than the downward edge an overbought SPX suggests.

In general, the VIX could be used to design short-term models to trade the SPX. But it is not clear that using VIX readings instead of SPX readings would enhance model returns. In fact, the more robust edges seem to simply be based on SPX movement itself.

Considering VIX-based Securities for Trading

As discussed earlier, VIX readings appear highly correlated to, and perhaps dependent on SPX action. High VIX readings are unlikely without high realized volatility in SPX. And low VIX readings are extremely unlikely when SPX is highly volatile. So rather than use VIX movement to identify edges for trading SPX, would there be more value in the converse? Could SPX movement be used to trade VIX-based securities?

First, let's recall that the VIX itself is not tradeable. But there are VIX futures, options, and exchange-traded products available for trading. So let's examine how some of these products have traded over time.

Below is a split-adjusted look at UVXY, which is the VIX-based ETF that has had the longest continuous history.

Figure 18

With the value dropping from over $24 billion in 2011 down to $8.44 at the end of 2023 there is a clear long-term downside edge. Of course, some very sharp countertrend rallies happened during big market selloffs. Still, a move from $24 million down to $8 seems like one that could be taken advantage of. And what is especially encouraging is that there was never a long, extended period between new lows.

Notable about UVXY is that the leverage changed from 2x to 1.5x on Feb 28, 2018, after "Volmageddon" in early February wreaked havoc on several VIX-based ETFs. UVXY went from a low of 4260 to a high of 15,090 (354% gain) during that period. During March of 2020 UVXY rose as much as 1300%. I am not going to get into position sizing and risk management in this paper, but it is clearly something that investment managers need to take into account when trading VIX-based products. Still, the long-term edge appears sizable.

Trading the ETFs and ETNs also includes counter-party risk, borrow costs, available shares for shorting, margin requirements, and ETF structure issues. These all create complications that I am not inclined to delve into in this paper, but have discussed elsewhere.

Most of these issues do not exist when looking at VIX futures (VX). Additionally, VIX futures have a longer history. And as shown below, it is not just the ETFs and ETNs, but also the futures, that have shown a long-term downside tendency.

Figure 19

This continuous futures contract was created with data available directly from the CBOE website. VIX futures expire on Wednesday mornings, so the roll from one month to the next was done at the close on Tuesday just before the Wednesday expiration. The price of the future declined from a roll-adjusted 229.9 on October 31, 2006 to 13.05 at the end of 2023. While there were sharp counter-trend moves along the way, the persistency was impressive. The largest and longest countertrend move occurred during 2008. Next we will zoom in on the 2007-2008 bear market as well as the 2022 bear market.

This chart shows the S&P 500 during the 2007 to 2009 bear market.

Figure 20

As you can see the S&P topped in October of 2007. The bear market bottomed in 2009, but it wasn't until May 2013 that SPX managed to make a new high. So a buy-and-hold S&P 500 strategy would have spent about 5 1/2 years in a drawdown during this bear market. But let's look and see what happened to VIX futures during this same period.

Figure 21

We see here that the bottom for the VIX futures did not come until May of 2008, a full 7 months after the initial S&P market top. There was a big spike during the bear market, but the recovery was much quicker. VIX futures made a new low in February of 2010. So rather than a 5 ½ year drawdown, a VX "short and hold" strategy would have only endured about a 1 ½ year drawdown. That's a massive difference, and it makes the idea of trading VIX-based products very appealing. When market shocks occur, you don't need a large SPX rally for a short-volatility strategy to make a new high. You just need the market to calm down enough to allow the downside tendency of VIX futures to reassert itself. Next let's look at the 2022 bear market.

Figure 22

The top panel is the S&P 500 from the beginning of 2022 through 2023. While SPX bottomed in October of 2022, it took until early 2024 to get back to a new high. It was a 2-year drawdown. The bottom panel shows VIX futures. VX barely went six months without making a new low. By the end of July 2022 it was already at new lows, and SPX had not even bottomed yet! When the SPX finally bottomed in October 2022, VX was just weeks away from another round of new lows. This persistent downside tendency creates a massive edge, and the shortened drawdowns make the thought of trading VIX-based products quite appealing vs trading the SPX.

Filtering VX Movement Using SPX/VIX Action

I established earlier that SPX is a better indicator than VIX for anticipating SPX movement. But what about VX movement? Next is a series of studies that utilize SPX readings and VIX readings and measure VX movement based on the same filters we used in evaluating SPX edges. It is important to keep in mind that since the long-term VX trend is down, these studies look at results of going SHORT VX. So a positive result means that VX has exhibited a downside edge under these circumstances. A negative result would indicate times the VX has risen.

Figure 23

Daily return stats shorting 1 @VX future using RSI(2) of SPX as a filter.
1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
0 Long-Term Filter	0 ST Filter	2	4278	58.11	0.05	213.52	-68.86	3.1	1.13
0 Long-Term Filter	RSI <= 20	2	822	62.9	0.22	178.6	-21.04	8.49	1.47
0 Long-Term Filter	RSI > 20 and <= 40	2	635	59.37	0.07	44.46	-36.87	1.21	1.16
0 Long-Term Filter	RSI > 40 and <= 60	2	603	59.87	-0.03	-18.18	-45.3	-0.4	0.94
0 Long-Term Filter	RSI > 60 and <= 80	2	851	59.69	0.06	54.21	-25.23	2.15	1.2
0 Long-Term Filter	RSI > 80 and <= 100	2	1367	52.89	-0.03	-45.57	-59.13	-0.77	0.89

These results are intriguing. We see that short-term oversold readings show favorable results and short-term overbought readings are unfavorable for the "short VX" trade. Without any filters, for the full period measured, VX declined 213.52 points (top row). By simply shorting VX when SPX posted an RSI(2) <= 40, and sitting out the rest of the time, more than all of the 213.52 downside points would have been realized. And that would have been accomplished by only being in the market 34% of the time! Also impressive is the fact that RSIs over 80 (bottom row) showed a 45.57 point gain in VX over time. This suggests that periods when SPX is short-term overbought are dangerous times to short VX, and they could even provide opportunities for taking long VX positions.

What if we use the RSI of VIX instead of SPX?

Figure 24

Daily return stats shorting 1 @VX future using RSI(2) of VIX as a filter.
1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
0 Long-Term Filter	RSI of VIX > 80 and <= 100	2	830	58.19	0.11	90.81	-33.12	2.74	1.24
0 Long-Term Filter	RSI of VIX > 60 and <= 80	2	686	57.14	0.05	31.98	-27.48	1.16	1.11
0 Long-Term Filter	RSI of VIX > 40 and <= 60	2	740	57.3	-0.03	-19.04	-58.22	-0.33	0.94
0 Long-Term Filter	RSI of VIX > 20 and <= 40	2	914	58.75	0.03	29.54	-36.87	0.8	1.09
0 Long-Term Filter	RSI of VIX <= 20	2	1108	58.66	0.07	80.23	-24.22	3.31	1.25
0 Long-Term Filter	0 ST Filter	2	4278	58.11	0.05	213.52	-68.86	3.1	1.13

As with the SPX tests we ran earlier, the edges here are not as consistent, nor as strong. An overbought VIX reading (> 80) suggests a favorable condition for "short VX". But the Avg Profit/Loss and Net Profits are about half of what is seen in the SPX RSI <= 20 results from the previous table. Also notable is that while an overbought SPX reading suggests a long VX edge, an oversold VIX reading does NOT. Using RSI of VIX as a filter does not appear nearly as valuable as using RSI of SPX.

I also broke out the returns by whether SPX closed above or below its 200ma. Here is the RSI of SPX breakdown.

Figure 25

Daily return stats shorting 1 @VX future using 1) whether SPX is above or below its 200ma, and 2) RSI(2) of SPX as filters.
1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
Above 200-day MA	0 ST Filter	2	3202	57.9	0.04	130.75	-29.84	4.38	1.14
Above 200-day MA	RSI <= 20	2	500	64.6	0.14	68.94	-17.89	3.85	1.35
Above 200-day MA	RSI > 20 and <= 40	2	453	57.84	0.08	38.29	-15.66	2.45	1.25
Above 200-day MA	RSI > 40 and <= 60	2	443	59.82	0.01	6.37	-22.41	0.28	1.04
Above 200-day MA	RSI > 60 and <= 80	2	677	59.97	0.05	30.72	-13.35	2.3	1.17
Above 200-day MA	RSI > 80 and <= 100	2	1129	52.97	-0.01	-13.57	-32.94	-0.41	0.95
Below 200-day MA	0 ST Filter	2	1076	58.74	0.08	82.77	-68.86	1.2	1.12
Below 200-day MA	RSI <= 20	2	322	60.25	0.34	109.66	-21.04	5.21	1.61
Below 200-day MA	RSI > 20 and <= 40	2	182	63.19	0.03	6.17	-36.87	0.17	1.05
Below 200-day MA	RSI > 40 and <= 60	2	160	60	-0.15	-24.55	-42.26	-0.58	0.83
Below 200-day MA	RSI > 60 and <= 80	2	174	58.62	0.13	23.49	-23.12	1.02	1.24
Below 200-day MA	RSI > 80 and <= 100	2	238	52.52	-0.13	-32	-44.95	-0.71	0.77

No surprises. Oversold in an uptrend is more consistent than oversold in a downtrend, but the instances below the 200ma show larger average moves.

Also notable is that the "upside VX" edge almost entirely plays out when SPX is in a downtrend (bottom row). Overbought in an uptrend stats only show small losses when shorting VX.

Next is the 200ma filter breakdown using RSI of VIX:

Figure 26

Daily return stats shorting 1 @VX future using 1) whether SPX is above or below its 200ma, and 2) RSI(2) of VIX as filters.
1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
Above 200-day MA	RSI of VIX > 80 and <= 100	2	610	57.38	0.04	23.17	-34.42	0.67	1.09
Above 200-day MA	RSI of VIX > 60 and <= 80	2	499	57.92	0.07	37.39	-10.82	3.46	1.25
Above 200-day MA	RSI of VIX > 40 and <= 60	2	551	56.62	0.01	2.91	-18.43	0.16	1.02
Above 200-day MA	RSI of VIX > 20 and <= 40	2	708	58.33	0.04	25.25	-15.58	1.62	1.13
Above 200-day MA	RSI of VIX <= 20	2	834	58.75	0.05	42.03	-24.56	1.71	1.22
Above 200-day MA	0 ST Filter	2	3202	57.9	0.04	130.75	-29.84	4.38	1.14
Below 200-day MA	RSI of VIX > 80 and <= 100	2	220	60.45	0.31	67.64	-23.74	2.85	1.5
Below 200-day MA	RSI of VIX > 60 and <= 80	2	187	55.08	-0.03	-5.41	-26.54	-0.2	0.96
Below 200-day MA	RSI of VIX > 40 and <= 60	2	189	59.26	-0.12	-21.95	-49.84	-0.44	0.84
Below 200-day MA	RSI of VIX > 20 and <= 40	2	206	60.19	0.02	4.29	-33.39	0.13	1.03
Below 200-day MA	RSI of VIX <= 20	2	274	58.39	0.14	38.2	-11.76	3.25	1.28
Below 200-day MA	0 ST Filter	2	1076	58.74	0.08	82.77	-68.86	1.2	1.12

The only strong edge here appears to be overbought VIX readings when SPX is in a long-term downtrend (blue outlined row). In looking at high VIX readings when SPX is above the 200ma (top row), the Avg Profit/Loss is the same as without any RSI filter above the 200ma. And the Drawdown and Profit Factor stats are worse.

This all suggests that RSI of SPX is a much better indicator of forward VX performance than RSI of VIX.

This last RSI table shows returns using 2, 3, and 4-period RSIs of SPX.

Figure 27

Daily return stats shorting 1 @VX future using RSI(2), RSI(3), or RSI(4) of SPX as a filter.
1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	rsiLength	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
0 Long-Term Filter	0 ST Filter	2	4278	58.11	0.05	213.52	-68.86	3.1	1.13
0 Long-Term Filter	RSI <= 20	2	822	62.9	0.22	178.6	-21.04	8.49	1.47
0 Long-Term Filter	RSI > 20 and <= 40	2	635	59.37	0.07	44.46	-36.87	1.21	1.16
0 Long-Term Filter	RSI > 40 and <= 60	2	603	59.87	-0.03	-18.18	-45.3	-0.4	0.94
0 Long-Term Filter	RSI > 60 and <= 80	2	851	59.69	0.06	54.21	-25.23	2.15	1.2
0 Long-Term Filter	RSI > 80 and <= 100	2	1367	52.89	-0.03	-45.57	-59.13	-0.77	0.89
0 Long-Term Filter	0 ST Filter	3	4278	58.11	0.05	213.52	-68.86	3.1	1.13
0 Long-Term Filter	RSI <= 20	3	457	64.33	0.27	125.44	-19.34	6.49	1.54
0 Long-Term Filter	RSI > 20 and <= 40	3	782	59.08	0.08	62.12	-42.23	1.47	1.17
0 Long-Term Filter	RSI > 40 and <= 60	3	944	59.11	-0.01	-7.42	-46.77	-0.16	0.98
0 Long-Term Filter	RSI > 60 and <= 80	3	1161	59.6	0.07	75.58	-25.52	2.96	1.21
0 Long-Term Filter	RSI > 80 and <= 100	3	934	51.39	-0.05	-42.2	-60.01	-0.7	0.83
0 Long-Term Filter	0 ST Filter	4	4278	58.11	0.05	213.52	-68.86	3.1	1.13
0 Long-Term Filter	RSI <= 20	4	285	64.21	0.3	84.78	-19.34	4.38	1.52
0 Long-Term Filter	RSI > 20 and <= 40	4	820	59.15	0.09	70.75	-39.63	1.79	1.17
0 Long-Term Filter	RSI > 40 and <= 60	4	1145	59.48	0.04	43.94	-51.57	0.85	1.09
0 Long-Term Filter	RSI > 60 and <= 80	4	1405	59.29	0.04	60.25	-25.6	2.35	1.15
0 Long-Term Filter	RSI > 80 and <= 100	4	623	48.8	-0.07	-46.2	-55.18	-0.84	0.71

The stats change some depending on the RSI length you use, but the implications remain the same. When SPX is short-term oversold, it is a favorable condition for shorting VX. And when SPX is overbought, VX shorting becomes dangerous, and long VX positions could even be considered.

Next let's look at times SPX closed at a high, a low, or in between. This series of tests is set up similar to the series shown earlier that examined SPX performance based on where SPX/VIX closed in relation to a new high, low, or in between. The first table below looks at SPX finishing hi-low-mid using a 10-day measure.

Figure 28

Daily return stats shorting 1 @VX future if SPX is 1) at Highest 10-day close, 2) Above 10-day MA but < Highest, 3) Below 10-Day MA but above Lowest, or 4) at Lowest 10-day close . 1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
0 Long-Term Filter	0 Filter - All Days	10	4278	58.11	0.05	213.52	-68.86	3.1	1.13
0 Long-Term Filter	1-Highest SPX Close	10	1114	52.6	-0.04	-41.78	-66.83	-0.63	0.86
0 Long-Term Filter	2-Above Avg SPX Close	10	1532	60.31	0.07	104.79	-20.4	5.14	1.22
0 Long-Term Filter	3-Below Avg SPX Close	10	1078	58.63	0.03	33.54	-59.41	0.56	1.06
0 Long-Term Filter	4-Lowest SPX Close	10	554	62.09	0.21	116.97	-22.06	5.3	1.41

Consistent with our other tests, a low SPX suggests a favorable time for shorting VX. A high SPX suggests an unfavorable time for shorting VX. Readings in between "highest" and "lowest" are not far from average returns. With middle quadrants not showing much edge (anywhere), the next several tests will focus just on "highest" and "lowest" readings.

The two tables below look at "short VX" performance broken down by "highest" and "lowest" close in the last "X Days". The first table uses VIX highs and lows, and the 2nd table uses SPX highs and lows.

Figure 29 & 30

Daily return stats shorting 1 @VX future filtered for instances where VIX closes at the lowest X day close or the highest X-day close.
1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
0 Long-Term Filter	1-Lowest VIX Close	5	1289	58.57	0.07	88.09	-24.9	3.54	1.23
0 Long-Term Filter	1-Lowest VIX Close	10	845	57.63	0.07	57.15	-11.15	5.13	1.25
0 Long-Term Filter	1-Lowest VIX Close	15	668	57.49	0.06	42.09	-15.3	2.75	1.25
0 Long-Term Filter	1-Lowest VIX Close	20	560	56.79	0.05	30.45	-12.96	2.35	1.22
0 Long-Term Filter	1-Lowest VIX Close	25	505	56.44	0.05	26.28	-11.25	2.34	1.22
0 Long-Term Filter	4-Highest VIX Close	5	978	58.9	0.14	136.01	-25.01	5.44	1.33
0 Long-Term Filter	4-Highest VIX Close	10	586	59.9	0.18	106.27	-26.54	4	1.4
0 Long-Term Filter	4-Highest VIX Close	15	445	58.43	0.16	71.12	-26.89	2.64	1.31
0 Long-Term Filter	4-Highest VIX Close	20	348	59.77	0.18	63.16	-28.58	2.21	1.31
0 Long-Term Filter	4-Highest VIX Close	25	293	59.04	0.15	42.9	-23.57	1.82	1.23

Daily return stats shorting 1 @VX future filtered for instances where SPX closes at the highest X day close or the lowest X-day close.
1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
0 Long-Term Filter	1-Highest SPX Close	5	1442	54.23	-0.02	-28.49	-56.14	-0.51	0.94
0 Long-Term Filter	1-Highest SPX Close	10	1114	52.6	-0.04	-41.78	-66.83	-0.63	0.86
0 Long-Term Filter	1-Highest SPX Close	15	993	52.06	-0.03	-27.08	-50.76	-0.53	0.89
0 Long-Term Filter	1-Highest SPX Close	20	904	52.43	-0.03	-23.4	-43.93	-0.53	0.89
0 Long-Term Filter	1-Highest SPX Close	25	852	52.7	-0.02	-21.21	-39.44	-0.54	0.89
0 Long-Term Filter	4-Lowest SPX Close	5	929	61.36	0.16	144.04	-37.9	3.8	1.32
0 Long-Term Filter	4-Lowest SPX Close	10	554	62.09	0.21	116.97	-22.06	5.3	1.41
0 Long-Term Filter	4-Lowest SPX Close	15	430	60.93	0.19	82.91	-23.63	3.51	1.35
0 Long-Term Filter	4-Lowest SPX Close	20	356	60.39	0.23	81.78	-21.04	3.89	1.41
0 Long-Term Filter	4-Lowest SPX Close	25	299	59.2	0.23	69.77	-21.04	3.32	1.39

The delineation in the bottom table is clearly better. It is all red near the top and all green near the bottom of the table. High SPX closes are a bad time to short VX (see the negative Avg Profit/Loss in the top 5 rows of the bottom table). Low SPX closes create opportune times for shorting VX. This can be seen by the strong Avg Profit/Loss numbers and other stats in the bottom 5 rows of the 2nd table.

Delineation in the top table was not nearly as impressive. High VIX readings showed a moderate edge for shorting the VIX. Low VIX readings did not provide a discernable edge. We keep seeing the same theme repeated.

Lastly, I broke down the SPX numbers to show how they looked above vs below the 200ma. This can be found in the table below.

Figure 31

Daily return stats shorting 1 @VX future filtered for instances where SPX closes 1) above/below 200ma and 2) highest/lowest X day close. 1/1/2007 - 12/31/2023.

Long-Term Status	Short-term Setup	Xdays	# Trades	% of Winners	Avg Profit/Loss	Net Profit	Max. Sys Drawdown	Recovery Factor	Profit Factor
SPX Above 200ma	1-Highest SPX Close	5	1177	54.12	-0.01	-12.4	-38.7	-0.32	0.96
SPX Above 200ma	1-Highest SPX Close	10	957	52.56	-0.01	-6.06	-23.53	-0.26	0.97
SPX Above 200ma	1-Highest SPX Close	15	872	52.29	0	1.49	-18.04	0.08	1.01
SPX Above 200ma	1-Highest SPX Close	20	809	52.53	0	-0.08	-17.57	0	1
SPX Above 200ma	1-Highest SPX Close	25	775	52.9	0	-1.81	-18.9	-0.1	0.99
SPX Above 200ma	4-Lowest SPX Close	5	592	61.49	0.09	52.65	-20.23	2.6	1.22
SPX Above 200ma	4-Lowest SPX Close	10	317	64.35	0.15	48.65	-17.57	2.77	1.35
SPX Above 200ma	4-Lowest SPX Close	15	223	63.68	0.15	33.21	-19.34	1.72	1.31
SPX Above 200ma	4-Lowest SPX Close	20	167	62.28	0.19	32.17	-11.46	2.81	1.44
SPX Above 200ma	4-Lowest SPX Close	25	121	61.16	0.2	24.16	-9.41	2.57	1.42
SPX Below 200ma	1-Highest SPX Close	5	265	54.72	-0.06	-16.09	-33.02	-0.49	0.9
SPX Below 200ma	1-Highest SPX Close	10	157	52.87	-0.23	-35.72	-45.98	-0.78	0.6
SPX Below 200ma	1-Highest SPX Close	15	121	50.41	-0.24	-28.57	-39.64	-0.72	0.59
SPX Below 200ma	1-Highest SPX Close	20	95	51.58	-0.25	-23.32	-33.08	-0.7	0.58
SPX Below 200ma	1-Highest SPX Close	25	77	50.65	-0.25	-19.4	-27	-0.72	0.55
SPX Below 200ma	4-Lowest SPX Close	5	337	61.13	0.27	91.39	-24.32	3.76	1.44
SPX Below 200ma	4-Lowest SPX Close	10	237	59.07	0.29	68.32	-21.04	3.25	1.46
SPX Below 200ma	4-Lowest SPX Close	15	207	57.97	0.24	49.7	-21.04	2.36	1.37
SPX Below 200ma	4-Lowest SPX Close	20	189	58.73	0.26	49.61	-21.04	2.36	1.4
SPX Below 200ma	4-Lowest SPX Close	25	178	57.87	0.26	45.61	-21.04	2.17	1.37

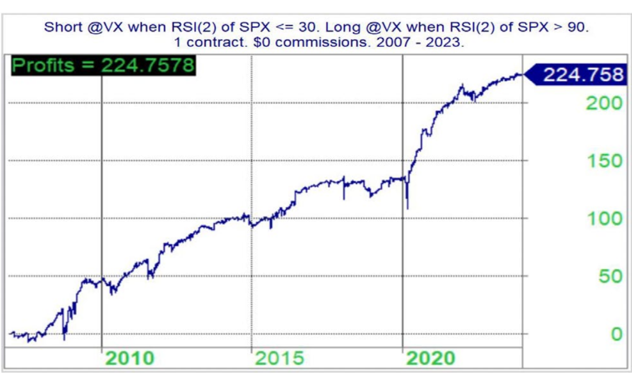
Like with RSI, 1) strong closes above the 200ma are basically neutral. 2) strong closes below the 200ma show a strong "upside VX" edge, 3) low closes above the 200ma show a high % Winners and muted drawdowns, while 4) low closes below the 200ma show the best Avg Profit/Loss statistics.

A View of a Simple Model

It is clear that there is ample opportunity in shorting VX (and other VIX-based products). The return breakdowns show that SPX action can be used to identify opportune times to take short (and long) VX positions. But while the data tables show net numbers and demonstrate the overall edges quite nicely, the consistency of the edges cannot be seen by simply looking at a data table. For that, a profit curve is helpful. I created a sample model based on the RSI results that were examined earlier. The rules are simple:

1) If the RSI(2) of SPX closes <= 30, short VX on close and hold the next day.
2) If the RSI(2) of SPX closes > 90, buy VX on close and hold the next day.
3) If neither of the above is true, then the position is flat.

Figure 32



The curve is not perfect, but it is certainly impressive. This was accomplished with just 1 measure (RSI of SPX). There was no filtering for uptrend/downtrend, even though our data suggested that could be used as well. The 225 points of profit are greater than the 213 points that VX lost over the period tested. And these results were accomplished despite only carrying VX exposure 45% of the time. The rest of the time the position would have been flat. Also notable is that the Max Drawdown in the model is 28.06 points. That is much lower than the 68.86 point drawdown for a "short and hold" approach. In fact, it represents a drawdown reduction of 59.25%!

None of this represents a complete system. But it is a solid start, and should help traders and managers consider implications of SPX movement on VIX-based instruments. Of course there are other factors that traders and investment managers will want to consider. These may include, but are not limited to, the VIX futures term structure, upcoming known event risks (elections, economic releases, etc.), and potential seasonality influences, as well as trading costs and tax consequences. Further, position sizing and risk management will need to be taken into account. But it is clear the SPX action can provide a quantifiable edge for trading VX. And it provides even better information than VIX action itself does for trading VX. Utilizing this concept should help traders and investment managers to develop winning strategies.

Conclusion

Lots of energy has been used over the years trying to understand what edges the VIX might provide in predicting SPX movement. While VIX readings can be used to identify compelling setups in many cases, it appears that overbought/oversold measures of the VIX are less predictive than using similar measures of SPX. Additionally, while most traders want to know where the SPX is headed, the easier question is "Where is VX headed?". The downside persistency of VIX-based products make them highly attractive for trading purposes. When a bear market arrives, drawdown lengths are often substantially briefer for a short-VIX position than a long-SPX position. In examining VX behavior, I again find that overbought/oversold measures of SPX provide better filtering than measures of VIX. I believe most traders have been getting it wrong for years. Rather than using the VIX to predict SPX movement, more substantial edges lie in using SPX to predict movement of VIX-based products.

According to Morris, Hessels, and Bishops 1968 paper *The relationship between hatching egg weight and subsequent performance of broiler chickens*, "Body weight to 12 weeks was found to be strongly related to egg weight, in a linear fashion, though this influence declined with age." So yeah…bigger eggs get you bigger chickens.

In their paper *Traits influencing the hatching performance of Japanese quail eggs,* Narahari, et al. state "Japanese quail eggs …from moderately heavier dams hatched slightly better than the eggs from lighter dams." They also noted that "Fertility and hatchability were directly proportional to the egg weight." So it appears bigger quails are going to give you a better chance at bigger quail eggs.

If bigger quails make bigger quail eggs, then bigger chickens will most likely make bigger chicken eggs. But thanks to Morris, I am more confident in saying that bigger eggs get you bigger chickens than I am saying bigger chickens get you bigger eggs. Based on my research, I am also more confident in saying that overbought/oversold SPX readings provide a sizable edge in anticipating VIX futures movement than I am saying overbought/oversold VIX readings provide a sizable edge in anticipating SPX movement.

While proper risk management needs to be implemented in any strategy, the techniques shared in this paper can be used to design profitable VX models, and even potentially greatly reduce drawdowns versus "short and hold". When utilizing measures of overbought/oversold on SPX, models can be created that effectively filter unfavorable conditions for attempting short-volatility trades, and can even be used to identify favorable opportunities for taking temporary long VX positions. By turning conventional techniques around, VIX traders can take advantage of the quantifiable edges that SPX movement provides.

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Technical Analysis for the Trading Professional, 2nd Edition

By Constance M. Brown, McGraw Hill, 2012

Review by: John Gajewski, Past President, Australian Professional Technical Analysts, Inc.

It doesn't take long for traders to realise that the one indicator or method they love, neither produces the consistent results they were expecting, nor gives them a proper grip on the market to generate consistent profits.

Constance Brown addresses these issues in her book *Technical Analysis for the Trading Professional*, with this second edition incorporating her learning experience since the first edition 14 years earlier. She is generous in sharing her extensive knowledge and experience into the analysis of market behaviour, throwing in many insightful observations along the way. On key techniques she also gives you the formulae to alter your charting system to display the adjustments she introduces.

As the title suggests, the book is aimed at the trading professional who is seeking greater precision and better timing in their trades. Novice traders should not be discouraged as there are still many takeaways for them. However, Constance does bring an enormous amount of knowledge and experience into each market analysis so without some broad experience of the market the discussion may feel a little overwhelming. But that is the price of precision and better timing – a lot of detail, history and hard work

Constance looks unfavourably upon the "Stochastic Default Club"[1] – those traders who unthinkingly accept software vendors' default settings for their indicators – and those traders who settle for approximations rather than aiming for precision. To stay on the right side of the trend, maximise profit potential and avoid the costs of stop-outs, hard, detailed, intelligent work is needed.

The book is organised in three parts. In Part One, Constance Brown addresses some misunderstandings of key indicators and methods and introduces the reader to a number of her unique parameter adjustments and overlays, especially with the use of oscillators. She introduces her custom Composite Index which is a variation on the popular RSI and explains how she uses the two together to sift through market opportunities and better identify the profitable trades, low-risk entry points and when to take profit. There are valuable insights on trendlines, cycles, moving averages, which are all directed to improving the quality of the trade entry.

Part Two is about price objectives. Considerable amount of time in this part is spent on Gann timing and target projection techniques, and even more time on Elliott Wave analysis and Fibonacci price projections. It is the proper understanding and exact calculations and projections from relevant points – which generally are not the price extremes – that will give the trader the edge he needs to turn opportunities into profit.

In Part Three, the shortest section of the book, Constance rounds off her methodology with a detailed description of her custom Composite Index, and insights on other useful aspects of the market, like volatility and depth of perception.

All the techniques discussed in the book are considered in every instance of analysis. Constance herself provides the best summary of her approach when she writes:

"The Elliott Wave Principle gave me a sense of what was coming and the size of the move. Gann analysis gave me a sense of when a move would happen. Fibonacci targets taught me price targets, correct leverage, and where I was wrong before I was stopped out. Oscillators added to the probability of being right and gave the needed permission to execute at a Fibonacci price target. But it was maturity that taught me not to be in the markets all the time. It was also experience that taught me we see things faster in charts than we will see them unfold in real life."[2]

This book is a valuable resource for anyone looking to deepen their understanding of the market, improve their entries and hold risk to a minimum.

Notes

1 Constance M Brown, Technical Analysis for the Trading Professional, 2nd Edition, 2012, p63.

2 *ibid.* p375.

Author Profiles

Nashwan Mohammed Al-Thawr, MFTA

Nashwan has more than 23 years of experience in financial markets analysis, technical analysis, options hedging strategies, trading equities, ETFs, futures, futures options, and crypto.

He is a former global stocks and derivatives strategist and one of the founders of the Investment Academy in 2005. Additionally, he has worked for the General Corporation of Social Security Funds as a finance and investment advisor and established the Investo4life fund as its CEO.

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Loïc is a financial executive at SNCF Voyageurs, the passenger division of France's national railway company. He specializes in management control, data analysis, and Business Intelligence, with a focus on digital transformation and finance modernization. In his role, he manages IT budgets exceeding €110 million, overseeing CAPEX and OPEX within Agile frameworks.

Certified as a Project Management Professional (PMP) and European Engineer (EUR ING), Loïc has 9 years of experience in railway engineering and 6 years in information systems and Agile methodologies. His MFTA research introduces innovative methods for quantifying trend strength and market sentiment, refining Renko chart analysis with volatility filters and financial ratios.

Certified by the AMF (French Financial Markets Authority), Loïc is passionate about financial markets and investment advisory. He also serves as President of the Savoie Section of MIF – Mutuelle d'Ivry, a mutual insurance organization. Additionally, he is a certified first responder and a licensed radio amateur, reflecting his commitment to community service and technology.

Nobuaki Kakimoto, CFTe, MFTA

Nobuaki has long been a prominent member of the Nippon Technical Analysts Associationβand an individual investor. His main interest has been in the field of Forex where he has used various technical analysis tools including his own creation since 2007.

As he has continuously traded using technical indicators, he has learned that a deep understanding of what the technical tools mean is essential to making trading decisions.

His MFTA thesis is a culmination of what he has learned through wide range of trading using technical analysis tools. He calls himself a newcomer in the field of technical analysis but desires to continue his research which would help traders break free from misconceptions and superficial understanding of technical indicators. His MFTA paper would be the first presentation of what he is aiming at.

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David is one of the UK's leading technical analysts and a well-known market commentator. He is the founder and CEO of Updata, based in London. He is the author of *Cloud Charts—Trading Success with the Ichimoku Technique*. He teaches the Ichimoku module for the UK Society of Technical Analysts Diploma Course, and he is a member of the American Association of Professional Technical Analysts. He is a partner at Betagroup, leaders in technical analysis training.

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Davide Pandini holds a Ph.D. in Electrical and Computer Engineering from Carnegie Mellon University in Pittsburgh, Pennsylvania. He was a research intern at Philips Research Labs in Eindhoven, the Netherlands, and at Digital Equipment Corp., Western Research Labs, in Palo Alto, California. He joined STMicroelectronics in Agrate Brianza, Italy, in 1995, where he is a Technical Director and a Fellow of STMicroelectronics Technical Staff.

Davide has authored and co-authored more than 50 papers in international journals and conference proceedings and served on the program committee of several premiere international conferences. He received the STMicroelectronics Corporate STAR Gold Award in 2008 and 2020, and the STRIVE Gold Award in 2022, for R&D excellence. Since June 2015, he has been the chairman of the ST Italy Technical Staff Steering Committee.

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Davide served as volunteer at the Universal Exhibition Expo2015—Feeding the Planet, Energy for Life—in Milano, Italy.

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Dr. Winter is a Berlin-based AI entrepreneur. He holds a doctoral degree and two B.Sc. degrees in Information Systems and Business Administration, all with distinction, from the Universities of Osnabrück and Marburg. His long-standing interest in methodological research and experimentation frequently finds application in trading. His contributions to the field have earned him five consecutive awards from the Association of Technical Analysts in Germany (VTAD). Despite this, he usually prefers not to trade himself because he believes that it is more efficient to create value than to trade it, especially since investors then have an incentive to work with, rather than against, each other.

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