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"Markets are never wrong – opinions often are."

—Jesse Livermore

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Letter From the Editor

By Dr. Rolf Wetzer, CFTe, MFTA

Dear Colleagues

One of the most iconic films ever is "Modern Times", a film produced, written and directed back in 1936 by the great Charlie Chaplin. Almost 100 years ago, large gear wheels were the epitome of progress. A technology that seems archaic from today's perspective.

We need to keep this in mind when we talk about artificial intelligence and other achievements today. There has always been progress driven by technological innovation. It is up to our children and grandchildren to judge how long-lasting our achievements will really be. We need to be open and curious in order to work with the new technologies of our generation and use them for ourselves. Without the willingness to learn, try and even fail, there will be no opportunities.

There are many opinions as to what exactly technical analysis is or is not. We are particularly adept at making distinctions. I understand this to mean the type of data we analyze and not the methods used. In other words, prices, returns, turnover or sentiment of market participants.

Our methods are very different and were always controversial in their day. What would a market participant from 1890 have thought of the first self-painted point-and-figure charts? Or of Charles Dow's theories? What did the traders of the 1920s think of wave theories? Or how were the first indicators evaluated? Or the first frequency analyses from the 1970s? We live in a time with more and more data and a variety of ways to access it. In addition, we have much more computing power at our disposal than ever before. New methods from other disciplines can be tried out and used. And yet, as long as we apply these techniques to market data, we are doing technical analysis.

The theme of this year's conference, "Exploring New Horizons in Technical Analysis", will focus on the evolving role of technical analysis in a rapidly changing financial landscape. That's the point. There is no old or new technical analysis. But there are new ideas that can be adopted without discarding the old, cherished approaches. Perhaps the textbooks need to be thicker, or the body of knowledge broader. Because our world just keeps on turning. But it can also be fun and broaden your own horizons. Perhaps chess is a good analogy. Grandmasters are the strongest players in the world. To achieve this status, they have always studied the game in all its facets, including its history. And yet today they learn and practise with powerful computers to test and question traditional strategies and rules.

I would like to thank everyone who made this journal possible. First and foremost, of course, are the authors. Again, we have a colorful mix of articles from colleagues, MFTA papers, an educational section from Italy, and our book review from Australia.

Next, we need to thank NAAIM and Susan Truesdale. By now it has almost become a tradition that we are allowed to publish their papers. This year we have the pleasure to feature Dr. Oliver Reiss, the winner of the NAAIM Founders Award. He is a member of the IFTA board and our John Brooks Memorial award winner of 2019.

A major contribution comes from Linda Bernetich's production team. Year after year, they pro-duce 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.

Best regards,
Dr. Rolf Wetzer, CFTe, MFTA

IFTA Journal

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"The Stochastic Oscillator Second Signal"

A significant signal justified and enhanced by Time Cycles

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1. Introduction

The price action is the primary data a technical analyst depends on in his analysis. This principle is originally based on Dow Theory's main tenet that states, *"The Averages discount everything",* (1) which means that the market price reflects every possible knowable factor that affects overall supply and demand. This theory was initially intended to be applied to market averages - seen as a measurement of economic conditions - it was later applied to individual stocks and all kinds of asset classes that are governed by free market demand and supply forces.

Although analyzing the price alone is valid, the fluctuations and randomness within price trends can create times of doubts, false signals, or uncontrollable volatility. For this reason, using technical analysis indicators along with price analysis is considered favorable and helpful.

A Technical Analysis indicator is a mathematical calculation for the price action, (2) designed to reveal potential strength or weakness that is not clearly shown on the price chart, assist in identifying reasonable entry and exit points and aims to isolate the price action from noise as much as possible. There are two main types of indicators: the Oscillators, which fluctuate between a bounded range, or unbounded but still oscillate around a central value, and trend following indicators, which usually move in trends like the price action.

Despite their tendency to support price analysis, technical indicators can also provide false or late signals. This issue of both price movement and indicator behavior is justified and can be avoided using time cycles.

Accordingly, in this article, a well-known Oscillator is chosen with a special signal that will be explained — one that works efficiently across different time frames and in various locations within different types of trends. This is the Slow Stochastic Oscillator Second Signal. Using this signal alongside with time analysis will enhance and confirm it. Interestingly, this signal is considered successful because it is generated by a specific situation within the time cycles "the Ripples effect".

The Stochastic Oscillator have been popularized By George Lane, who has been using it in his investment educators since the 1950s. (3) The stochastic Oscillator consists of two lines, %K and %D, and has two versions: the fast one and the slow one. The slow version uses the %D line of the fast version (which is a moving average for %K) as its %K slow. Then it creates another moving average for the %K slow to produce its %D slow. After long usage and observation, the slow version is considered more reliable and representative for market movements compared to the fast version. A very good, recommended parameter set — which will be used in this article — is 9-period, with a 5-period moving average (%K Slow) and 3-period moving average (%D slow).

This article is divided into six sections. The following section reviews the market movement dilemma, discussing the problem of randomness in price trends that leads to bull and bear traps, failure of classical price patterns and the shortcomings of the buy/sell or strength/weakness signals provided by different technical analysis indicators. Section 3 illustrates how that market movement is justified and explained by time cycles, and how time cycle analysis can help avoid such issues. Section 4 focuses on the Slow Stochastic Oscillator (9,5,3) (SSO thereafter), its structure, calculation, and advantages. Sub-section 4.1 explains the relation between the SSO and time cycles, and why the 9-period was chosen. Sub-section 4.2 highlights the drawbacks or failures of SSO crossovers, and then introduces the significance of SSO second signal. Sub-section 4.2.1 presents specific rules to identify and act upon the SSO Second signal in both uptrends and downtrends. In 4.2.2 we explore the SSO second signal locations in the trend, and its implications. Section 5 demonstrates how applying time cycles enhances and confirms the SSO second signal across all trend locations. Sub-section 5.1 offers a deep explanation for the success of the SSO second signal, justified by the main principles of time cycles. Section 6 summarizes and highlights the main takeaways the reader should retain from this article.

Before we start, I must acknowledge and thank the person who first shared with me the parameters used in this indicator: my mentor, Mr. Saleh Nasser, Head of the education committee at both the International Federation of Technical Analysts (IFTA) and the Egyptian Society of Technical Analysis (ESTA). When I asked for his permission to mention him in this article, he kindly agreed and added that he himself had learned these parameters from the late Mr. Hani El Sergani — may he rest in peace — a professional portfolio manager and one of the earliest adopters of technical analysis in Egypt. Interestingly, as will be stated within the article, this period (from 9 to 12) was also recommended by others. The main point of our article is not the specific period used, as the signal remains valid even with different periods, but it is very important to refer to those who originally used and passed down these parameters.

2. The market movement dilemma

The market moves in a random trending manner — this is the main description someone could give about market action in any time frame. A bull trend that lasts for a year has days, weeks and sometimes even months that move downward against this upward trend. On the other hand, a short-term downtrend that lasts for three weeks has minutes, hours and even days that move to the upside against the direction of this downward trend.

The technical Analysis justification for such movements is that the market does not move in a straight line, (4) but in zigzag shape. This shape is constructed by demand and supply forces, which are displayed on any chart as bottoms (demand) and peaks (supply), and the direction of those bottoms and peaks is the guide for the trend direction.

The problem is that to rely on this simple definition of the market direction to take an investment decision and act accordingly, it will assume that the market forces (demand and supply) have the same time span but different directions. For example, it the trend is up over a three-week span, this would mean that the short-term buyers are stronger than the short-term sellers. So, if the market creates a new peak to the upside, it will confirm this trend direction and the right decision would be to buy. But unfortunately, this is not necessarily — and not usually - the case, because the market action is made up not only of buyers and sellers, but also reflects that action of many different types of investors in terms of time span (very long-term, long-term, medium-term, short-term, very short-term and day to day investors). That is why investment decisions are very hard to make — we are dealing with a market constructed from huge number of investors who differ both in direction and in time span.

This dilemma can be seen in many situations, such as:

1-A market/stock bull trap or bear trap

when the market breaks a resistance to the upside and then started to go down again in the opposite direction (vice versa).

The following chart displays an example of such a situation. It shows the daily chart of the Dow Jones Industrial Average, presenting a clear uptrend achieving a new upside breakout and indicating that buyers are in control.

The following chart shows an update of the above chart, highlighting a re-violation of the previous peak to the downside and a significant shift in market direction (Bull trap).

Chart 2: The Dow Jones Industrial Average (.DJI) Daily candlestick chart (update)

It is also important to note the first decline from the top, where the market broke below a previous bottom — this point is marked with a circle in the chart above. It signaled the strength of the sellers. Yet despite this bearish trigger, the market rallied once again, retesting the previous high (Bear trap) before eventually resuming the decline and confirming the start of a new bearish trend.

2-The failure of classical price patterns

Another example of the price-action dilemma is the failure of classical reversal or continuation patterns. The following example illustrates how a confirmed classical reversal pattern can sometimes succeed and at other times completely fail.

Chart 1: The Dow Jones Industrial Average (.DJI) Daily candlestick chart

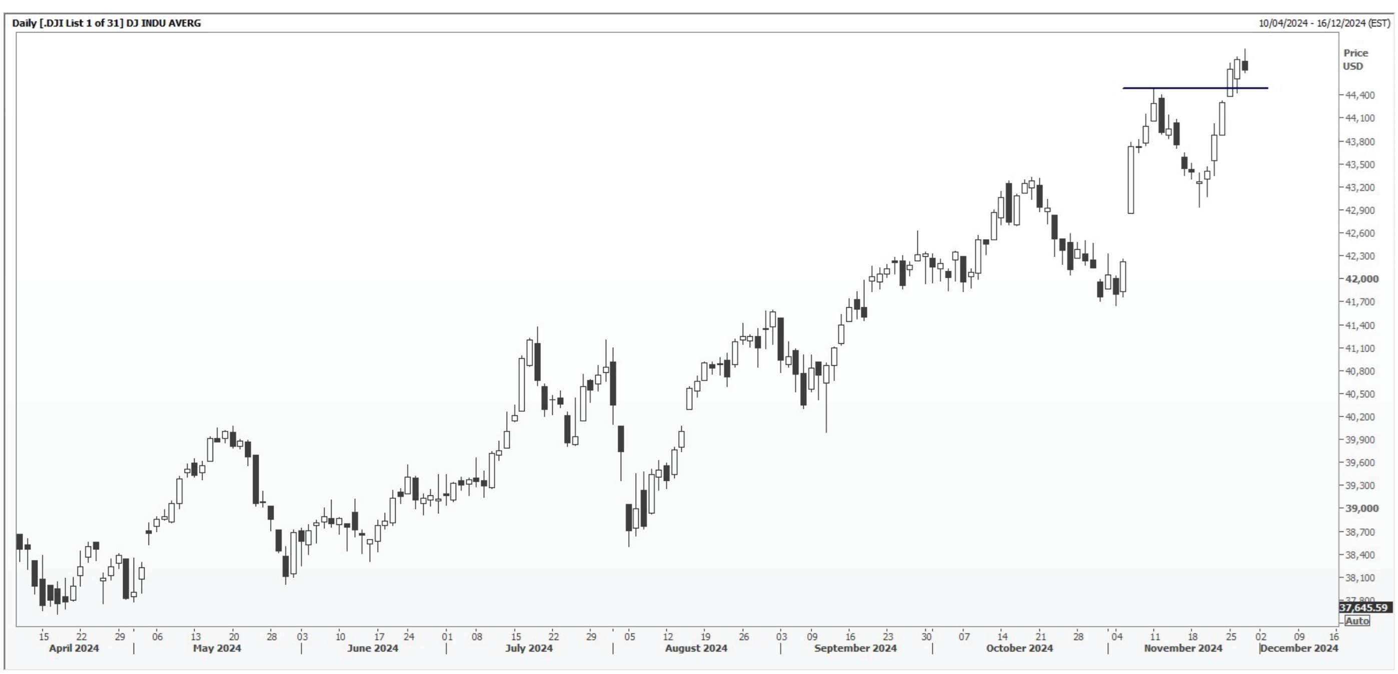


Chart 3: Gold (XAU=) Monthly candlestick chart

As Shown in the chart above, Case 1 presents a textbook "Triple Top" reversal pattern in Gold, with lower highs and a decisive monthly close below the neckline. The signal proved successful, as Gold continued to decline for more than three years.

However, in Case 2, Gold formed a clear "Double Top" reversal pattern, with same highs and a monthly close below the neckline - yet this time, the signal failed. The market broke the violated support to the upside again, made a new high and resumed its previous uptrend.

Some theories have attempted to explain such inconsistencies. For instance, Elliot Wave Theory might interpret Case 1 as a motive downward wave within a larger corrective phase, while explaining Case 2 as a corrective (zigzag) wave that it is part of a bigger motive wave. (5) However, these interpretations tend to describe market action after the fact, rather than predict it. If, for example, Gold had continued to decline in Case 2, it could have equally been labeled a motive wave or part of a complex correction. This illustrates a key difference between Classical Technical Analysis and Elliott Wave Theory: the former assigns a fixed implication to a pattern, while the latter can justify alternative outcomes retroactively by adjusting the wave count.

To further illustrate: in an uptrend, a Descending Triangle pattern appearing on any stock chart would be interpreted as bearish under classical analysis. If the stock rises instead, it will be considered a failed pattern. On the other hand, as Jhon J. Murphy explained, under Elliott Wave, however, that same triangle (as a corrective wave) might be considered bullish. They are bullish in the sense that they indicate resumption of the uptrend (despite its descending structure). He also noted that *"Elliott Wave Theory also holds that the fifth and last wave within the triangle sometimes breaks its trendline, giving a* ***false signal,*** *before beginning its "thrust" in the original direction."* (6)

The purpose of highlighting this Gold chart example, especially using the monthly time frame, is to show that the challenge of false signals and pattern failures exists even on major time scales and with seemingly strong confirmations. In fact, such failures are even more common on lower time frames and with smaller patterns, where false breakouts and whipsaws become increasingly frequent. And as Charles D. Kirkpatrick and Julie R. Dahlquist mentioned *"Breakouts occur when prices pass through specific levels. Because these levels are often somewhat unclear zones and because* ***false breakouts are common****, the point at which a breakout occurs is extremely important".* (7)

3-Indicator false or late signals

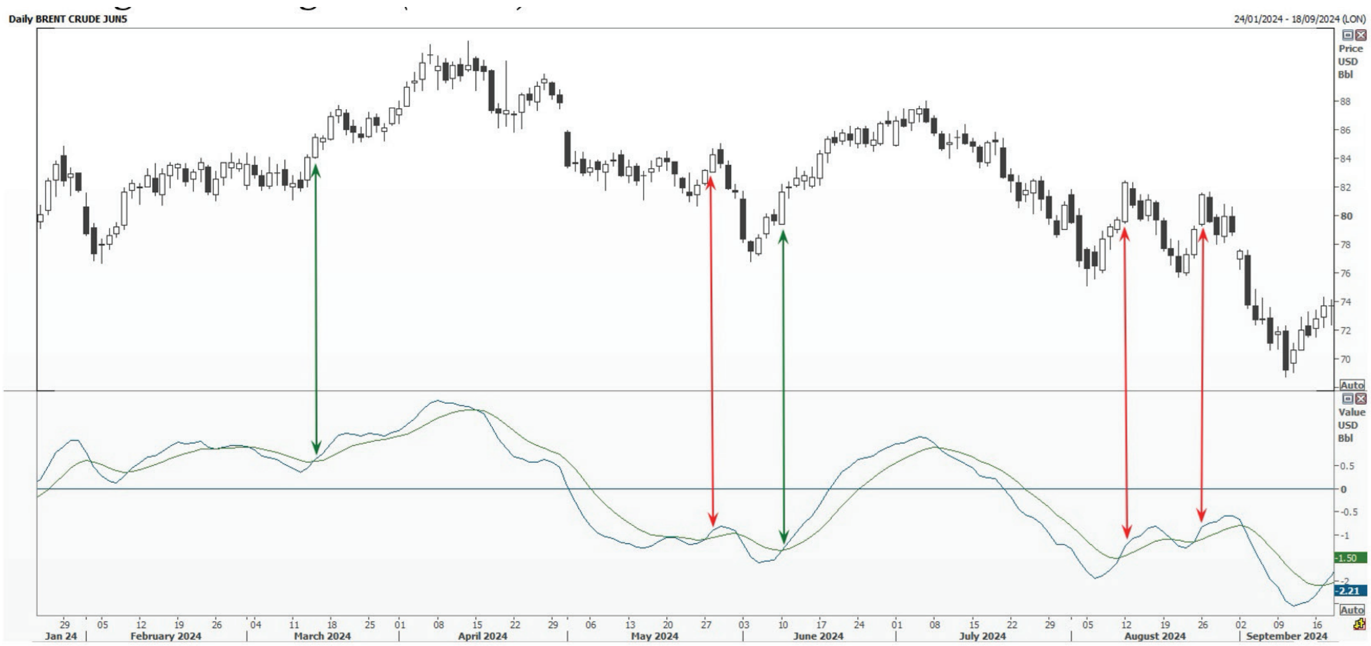
The third situation - which is highly relevant to the focus of this article — is the success and failure of the buy/sell or strength/weakness signals generated by technical indicators. Due to the price dilemma discussed earlier, Technical Analysis indicators have three main objectives:

- To reveal potential strength or weakness that is not clearly shown on the price chart.
- To help in identifying reasonable entry and exit points.
- To isolate the price action from noise

However, technical indicators can also fall victim to the same challenges as price patterns - false breakouts, failed signals, and late signals.

The following example will demonstrate the issue of failed signals in more details.

Chart 4: Brent Crude (LCOc1) Daily candlestick chart along with Moving Average Convergence Divergence (MACD) indicator



As shown in the chart above, the use of MACD crossover signals on Brent Crude between February 2024 and September 2024 illustrates this problem. If we focus solely on the bullish crossovers, we find one successful signal during an uptrend and another one during downtrend, which merely triggered an upside correction. At the same time, there were three failed buy signals — despite the crossovers, the market continued its decline. The natural question that follows is: Why?!

3. Market motion as justified by Time cycles

As previously discussed, the market is composed of various types of investors - different not only in directional bias but, more importantly, in time horizon. For example, if a day trader is bullish, that means he intends to buy and then sells within the same day, ideally at a higher price. However, if the market doesn't rise within that timeframe, he will likely exit his position before the close. This logic applies across the entire investor spectrum, from intraday traders to long-term institutional investors.

This concept is explained by the summation principle in time cycles, which states that all price movement is the simple addition of all active cycles. (8) This principle offers a powerful explanation for the dilemmas of price movement discussed in the previous section. By understanding how different cycles interact, we gain clarity on why price action can seem contradictory or unreliable in different situations and various time frames.

Let's examine how this summation principle influences market movements, and what are the different combinations that will cause this market behavior.

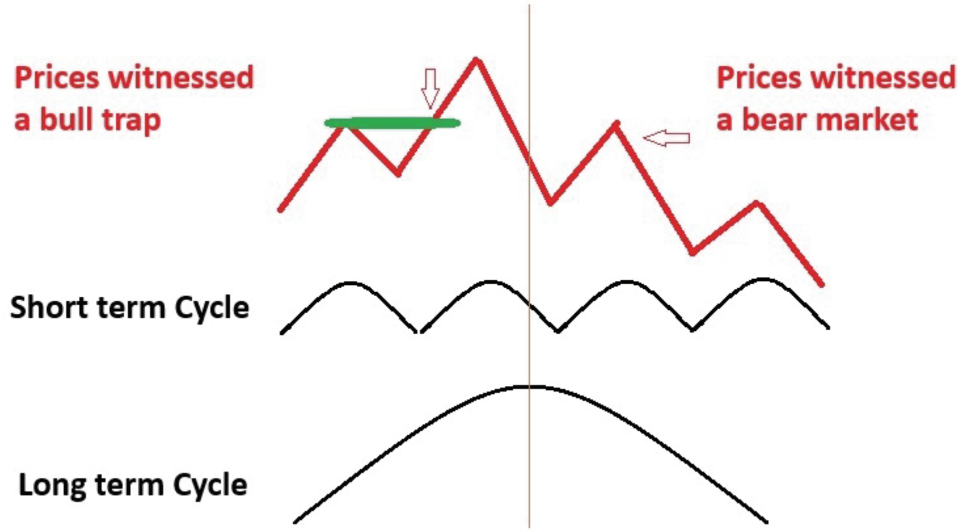
First situation: A market/stock bull trap or bear trap

The most crucial factor in interpreting market direction is identifying the dominant, or long-term cycle. A bull trap typically occurs when the short-term movement or cycle is positive, while the longer-term cycle is reversing or already falling. This divergence results in temporary price strength that fails to follow through - leading to a trap, as was seen in Chart 2 when the Dow Jones Industrial Average reached a new high but quickly reversed direction.

On the other hand, a bear trap emerges when the short-term movement or cycle is negative, while the longer-term cycle is reversing upward or already rising.

The following figure demonstrates how the price movement can be interpreted as the sum of two different time cycles, shedding light on the mechanisms behind such traps.

Figure 1: Price movement resulting from the summation of two different time cycles



By Observing Figure 1 above, we see it is divided into three layers, from bottom to top:

- The first part shows a long-term cycle.
- The second shows a shorter-term cycle.
- The third represents the price action resulting from the summation of both cycles.

On the left side of the figure, the long-term cycle is in a rising period. As a result, each time the short-term cycle dips, price experiences a correction or higher low, only to rise again and achieve new highs. Despite the last upward breakout, the price suddenly reverses sharply, breaking previous support to the downside. This decline or reversal is clearly justified by the combine effect of the short-term cycle turning down while the long-term cycle shifts from rising to falling. This is precisely what occurred in the Dow Jones Industrial Average example discussed earlier.

On the right side of the figure above, the long-term cycle is already declining making the overall price trend to downtrend. Each time the short-term cycle rises, it merely produces a temporary corrective rally, creating lower highs before continuing the downtrend and achieving new lows again.

Second situation: The failure of classical price patterns

I recommend readers refer to IFTA Journal, 2021 edition, where I have explored this concept in detail in my article titled *"The Ripples Effect: A Clearer View for Market Action and Price Patterns"*. In that piece, I introduced a new way of interpreting classical price patterns, renaming them price ripples. This term explains classical price patterns that they are created *because of the collision of two or more different trends (different in time and direction), the following direction of any price pattern is based on the direction of the longer-term trend not on the structure or shape of the pattern.* (9) This explains why some classical patterns succeed while others fail, and what was also described by the Elliot wave theory as the correct count versus the alternative count. Simply put: no price pattern should be inherently labeled bullish or bearish, the real practical reason of witnessing such patterns is the collision of two or more different cycles, its outcome depends on the underlying time cycles direction, particularly the dominant or longer-term cycle.

To better visualize this, let's revisit the Gold chart below, but this time with a 50 month centered envelopes with 20% margins overlaid, to represent the long-term cycle.

- In Case 1, a Triple top pattern was created because Gold was transitioning from a rising to a falling long-term cycle. The shorter-term upward moves clashed with the dominant cycle downward reversing movement, resulting in a successful reversal and downtrend that lasted for more than three years.
- In Case 2, a Double top pattern, appeared with a short-term cycle that was moving downward, but the longer-term cycle was still rising. This cycle alignment caused the apparent breakdown to reverse, producing what is often called a false break, followed by a continuation to new highs.

Chart 5: Gold (XAU=) Monthly candlestick chart along with 50 Month Centered Envelops with 20% margins

To effectively monitor, identify, and visualize the different types of market cycles, as demonstrated in the previous example — since a full treatment of cycle identification methodology is beyond the scope of this article - I recommend referring to the article previously mentioned (*"The Ripples Effect: A Clearer View for Market Action and Price Patterns"* published in the IFTA Journal, 2021 edition).

Third situation: Indicator false or late signals

Technical analysis indicators rely entirely on price data, yet as previously discussed, price is itself the result of multiple overlapping cycles acting simultaneously in the market. Therefore, it becomes crucial to understand that the reliability and timing of indicator signals depend on their alignment with the prevailing direction of dominant time cycles.

Early signals provided by indicators may appear promising but can fail if they emerge in opposition to the larger, underlying cycle. On the other hand, signals that occur in harmony with the dominant trend or longer-term cycle have a significantly higher chance of success.

To illustrate this clearly, let us revisit the Brent Crude chart below, this time with a 30 day centered envelope applied with 4–5% margins to reflect the relatively longer-term cycle. We can now see that the failed buy signals occurred when the dominant cycle was still declining. Conversely, the successful signals occurred during the upward phases of this dominant cycle.

Chart 6: Brent (LCOc1=) Daily candlestick chart along with 30 Days Centered Envelops with 4-5% margins

In the remainder of this article, we will narrow our focus to a specific technical indicator and a specific well-defined successful signal. We will see how this signal is explained and enhanced according to our understanding of the effect of different time cycles on the market action. This approach not only validates the signal in question but also sets a framework for using technical indicators more effectively across market conditions.

4. Slow Stochastic Oscillator (recommended 9, 5, 3)

The Stochastic Oscillator is classified as a price location indicator, as it measures the position of the current closing price relative to the high-low range over a specific period. While the 14-period is commonly used, I recommend applying the SSO with a 9-period, using a 5-period moving average for the %K slow and a 3-period moving average for the %D slow.

This particular configuration ensures that significant market cycles are effectively represented by the SSO, this concept will be explored in greater detail in the following subsection.

Interestingly, Charles Le Beau notes in his book Technical *Traders Guide to Computer Analysis of The Futures Market: "Our Experience and testing show the 9 to 12 range to be the best compromise between the speed of the signals (%K crossing %D) and the validity or follow through that produces the least amount of false signals"* (10)

The chart below illustrates the structure, calculation method, overbought and oversold zones, and overall advantages of using the SSO (9,5,3).

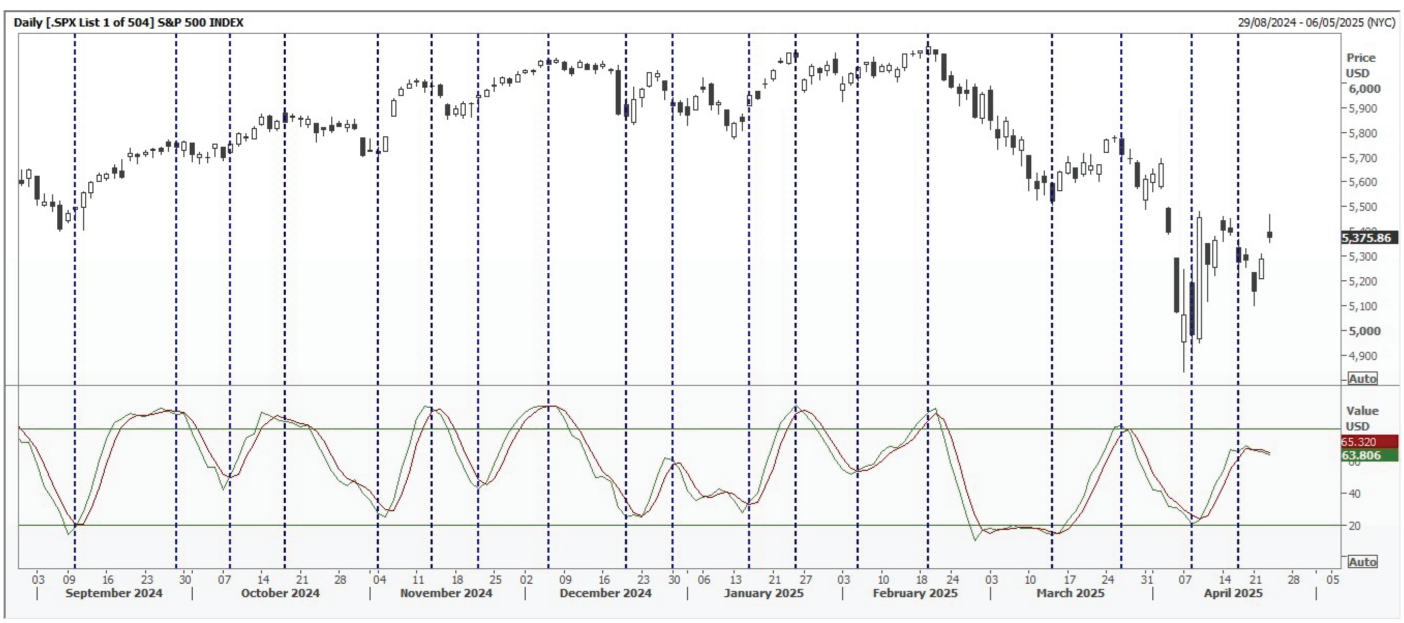
By examining the chart above we can observe the following key points:

1. The SSO oscillates between 0 and 100.
2. The indicator consists of two lines: %K (the 5 days moving average of Close (today) – Lowest Low / Highest high – Lowest Low over a period of 9 days) and %D (the 3 days moving average of %K).
3. The overbought area is defined as the area between 80 and 100, while the oversold area lies between 20 and 0.
4. As indicated by the vertical dotted lines on the chart, since SSO is a price location indicator, it closely tracks price movement. When the market forms a bottom and starts to rise, %K (green line) typically crosses above %D (red line), generating a bullish crossover signal and both lines move upward. Conversely, when the market forms a peak and starts to decline, %K (green line) crosses below %D (red line) forming a bearish crossover and both lines move downward. Although these signals can sometimes lag the price action, they still mirror the general price movements quite obviously.

4.1 Slow Stochastic Oscillator and Time Cycles

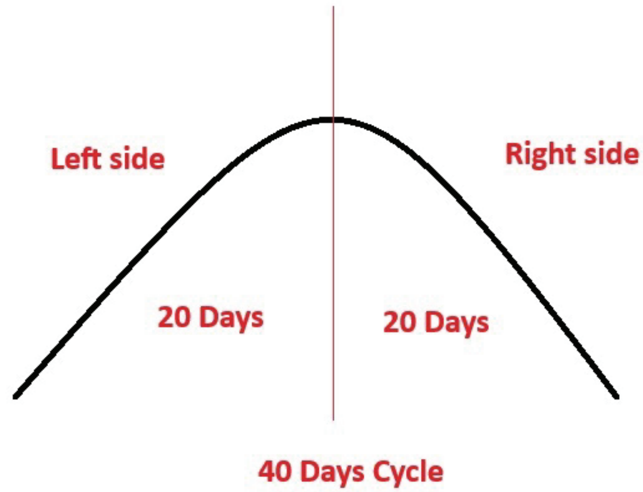
As previously discussed, time cycles play a critical role in shaping price behavior. Identifying these cycles – especially the dominant ones - is very important in investment decisions, even though it is not a simple task.

Chart 7: S&P500 (.SPX) Daily candlestick chart along with Slow Stochastic Oscillator (9,5,3)



A complete or rhythmic time cycle is defined as *"a cycle which repeats itself at rather uniform time intervals. Rhythm implies a kind of a beat".* (11) This cycle is divided into two phases, the left-hand side which represents the rising part and the right-hand side which represents the declining part. Figure 2 below illustrates a simplified representation of a one complete cycle.

Figure 2: A simple example of one complete time cycle with a 40-day span



Since the cycle is hypothetically divided into two phases - one rising and one falling – using any technical indicator with a span equal to the full cycle (e.g. 40 days in this example), it will eliminate this cycle. (12) The indicator averages both the rising and falling movements, causing the cycle to disappear from the indicator's output.

On the other hand, applying a technical indicator with a period equal to at least half the cycle's span allows the cycle to appear in the indicator's output. This is because the technical indicator will reflect the rising and falling phases separately. (13) That is why many technical indicators adopt a 14-period span to capture fluctuations of a short-term monthly cycle.

In this context, to show this short-term monthly cycle or even the shorter-term fluctuations, SSO with a 9-period span was selected. As demonstrated in chart 7, the SSO closely follows most of the market movements, effectively highlighting the underlying short-term cycles. This is our preferred configuration, but even the commonly used 14-period default will produce a comparable output, though with slightly less sensitivity.

An interesting and practical benefit of using the SSO (9,5,3) is its ability to help pinpoint the bottoms of a specific price cycle. The following chart illustrates this concept:

Chart 8: EURO versus USD Dollar (EUR=) Daily candlestick chart along with Slow Stochastic Oscillator (9,5,3)

As shown in the chart above, the oversold SSO crossovers correspond to price bottoms (red arrows), which serve as starting points for identifying a repeating cycle. By measuring the time between successive bottoms marked by SSO crossovers, we observe a cycle length of approximately 38-40 days. This cycle is repeated in future price action, with each subsequent bottom coinciding with another SSO crossover, confirming the reliability of the tool in highlighting cyclical bottoms.

4.2 Slow Stochastic Oscillator Second signal

After the illustration of the structure of the SSO, calculation, and practical advantages – particularly its use in identifying price movements and time cycles - let us now explore a valuable buy/sell signal that we figured it out.

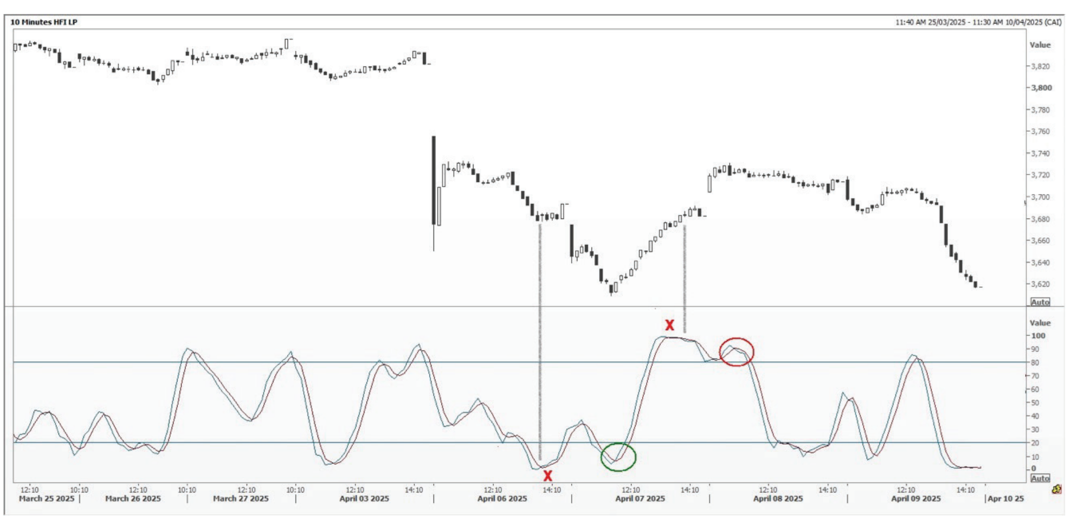
As previously mentioned, SSO crossovers always reflect price movements. However, in many cases, the signals are either lagging or the price reaction following the signal is too weak to justify trading on it. The following chart highlights this drawback:

Chart 9: Microsoft Corp (MSFT.O) Daily candlestick chart along with Slow Stochastic Oscillator (9,5,3)

In this example, several SSO crossovers (indicated by blue arrows) proved to be unprofitable, as the subsequent price moves were minimal. In some cases (indicated by red arrows), the signals were significantly lagging, generating buy signals near the top or sell signals near the bottom of the move. While some other SSO crossovers were successful, but with the lack of a clear rule to distinguish between them poses a challenge to identify and follow.

However, through detailed observation, we identified a particularly reliable signal using the SSO, *"Ignore the first crossover that appears in the overbought or oversold zone, and act upon the second one".* Let's examine the following example to illustrate this insight:

Chart 10: Hermes Last Price Index (.HRMSL) - Egyptian Stock Market- 10-minutes candlestick chart along with Slow Stochastic Oscillator (9,5,3)



As shown in the chart above, while the index was moving in a downtrend, the SSO entered oversold area and generated a buy signal (marked with an "X"). However, the price barely reacted, or the movement was too weak to capitalize on. This is the first crossover or signal, which we should ignore.

Shortly after, the SSO rose slightly, produced a negative crossover, then dropped again into the oversold area and finally generated "the second buy signal". This is the signal to act upon. As can be seen, the signal occurred near the actual price bottom and was followed by a strong and meaningful upward movement.

The other situation unfolded on the upside, after the index rallied and broke above the resistance, the SSO entered overbought area and generated a sell signal (also marked with an "X"). Again, the price did not decline significantly. The SSO then dipped slightly, formed a positive crossover, and reached back the overbought area, and then generated "the second sell signal". This is the signal to act upon. As can be seen, the signal occurred near a notable a price peak and was followed by a significant decline.

4.2.1 Slow Stochastic Oscillator Second signal rules

Generally, the second SSO crossover is highly significant, it often signals that a strong move is about to begin. Even in cases where the signal does not result in a major move or fails, it usually appears very close to the end of the trend under study, offering early positioning benefits.

To formalize this signal and reduce emotional or subjective interpretation, a set of specific rules is recommended to systematically identify and act upon the SSO second signal. These rules are as follows:

In case of an uptrend:

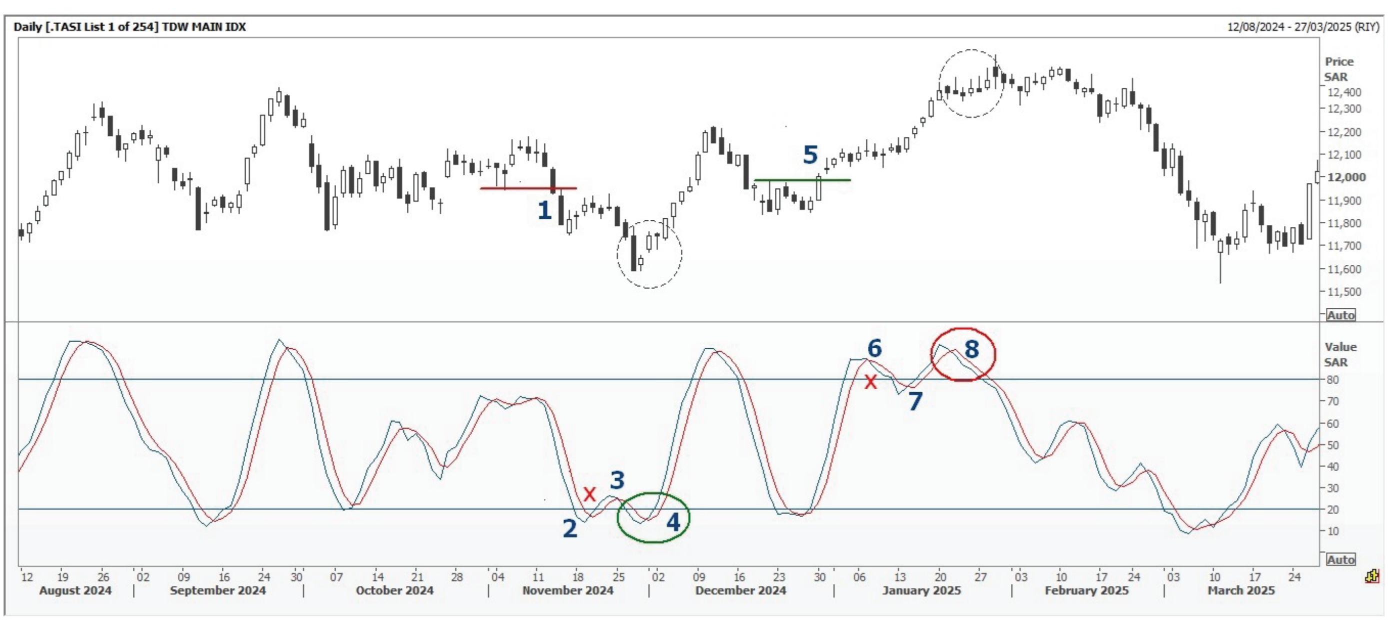
1. The price is trending upward, confirmed by a break above previous peak.
2. The SSO reaches overbought area and provides a sell crossover signal. (It is preferable if it declines below 80 level, but this is not a strict requirement, and it should not reach oversold area). At this stage, the subsequent price movement is usually insignificant.
3. The SSO provides a buy crossover again and attempts to reach overbought area once more. Most of the time, this is accompanied by a new high in the price.
4. The SSO then provides the second sell crossover signal from the overbought area (whether above 80 level or slightly below 80 level is acceptable). This is the signal we should act upon by selling the asset under study.
5. The re-entry level (to cover the short or re-buy) should be set above the last price peak that corresponds to the SSO's second sell crossover.

In case of downtrend:

1. The price is trending downward, confirmed by a break below previous bottom.
2. The SSO reaches oversold area and provides a buy crossover signal. (It is preferable if it rises above 20 level, but this is not a strict requirement, and it should not reach overbought area). At this stage, the subsequent price movement is usually insignificant.
3. The SSO provides a sell crossover again and attempts to reach oversold area once more. Most of the time, this is accompanied by a new low in the price.
4. The SSO then provides the second buy crossover signal from the oversold area (either below 20 level or slightly above it). This is the signal we should act upon by buying the asset under study.
5. The stop-loss level should be placed below the last price bottom that corresponds to the SSO's second buy crossover.

The following chart will demonstrate and apply the above-mentioned rules in the two uptrend and downtrend scenarios:

Chart 11: Tadawul FF Index (.TASI) - Saudi Stock Market - Daily candlestick chart along with Slow Stochastic Oscillator (9,5,3)



Let us examine the chart above - where both situations happened successively - step by step, as annotated:

Point 1: The price was in a downtrend, confirmed by breaking below previous bottom.

Point 2: The SSO reached oversold area and provided a buy crossover (it rose above the 20 level). Note how the following price move was insignificant.

Point 3: The SSO gave a sell crossover and returned to the oversold area again, and the price made a new low.

Point 4: The SSO provided the second buy crossover. This is the valid buy signal. The entry was near the bottom (highlighted with a dotted circle), and the price rose significantly afterward. Stop-loss should be placed below the last bottom.

Point 5: The price was in an uptrend, confirmed by breaking above previous peak.

Point 6: The SSO reached overbought area and provided a sell crossover (it declined below the 80 level). Note how the following price move was insignificant.

Point 7: The SSO gave a buy crossover and returned to the overbought area again, and the price achieved a new high.

Point 8: The SSO gave the second sell crossover. This is the correct signal. It appeared early, close to the top (again marked with a dotted circle) and was followed by a significant downward move. The re-entry level should be placed above the last peak.

4.2.2 Slow Stochastic Oscillator Second signal - trend location

When and where should we expect to witness an SSO second signal?

Despite having precise rules for identifying this signal, what's truly remarkable is how frequently the SSO second signal appears across different markets, timeframes, and price trends. It is almost always present!

The following examples demonstrate the presence of this signal in different markets, different time frames and accordingly will have different impact. The SSO second signal may appear in the following situations:

1-At the start of a main bottom:

In this case, the signal often suggests the beginning of a trend reversal to the upside. It typically appears on the same timeframe as the price chart understudy. It is worth noting that some short-term volatility or temporary movement against the signal may occur, but it will be temporary, and the signal remains valid.

Chart 12: Orascom Construction (OCIC.CA) - the Egyptian Stock market - Weekly candlestick chart along with Slow Stochastic Oscillator (9,5,3)

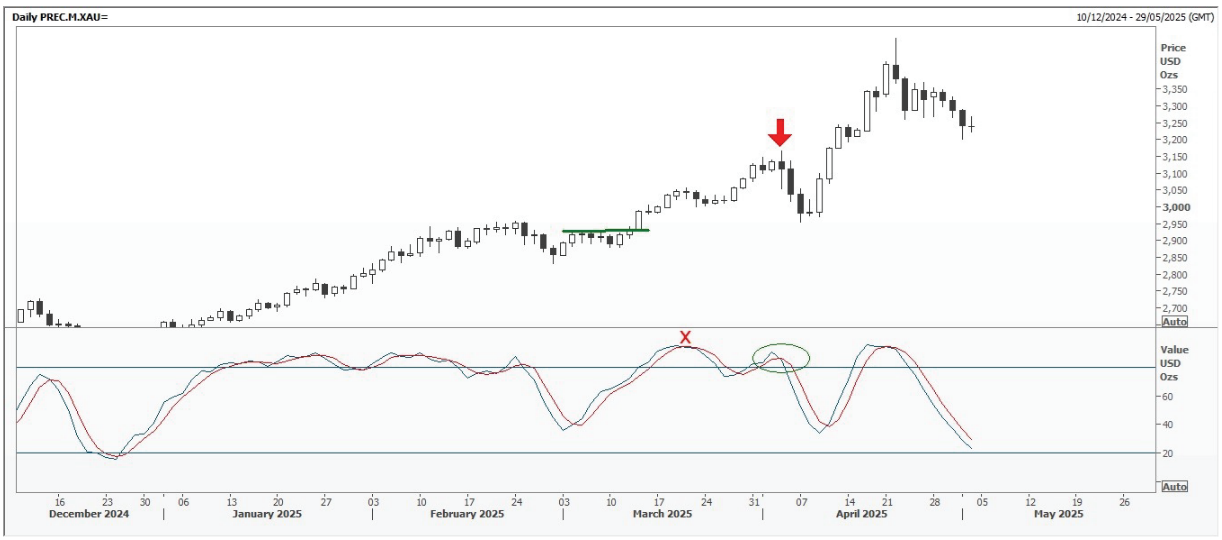
As shown in the weekly chart above of OCIC, following the severe decline during the 2008 financial crisis, the stock bottomed in December 2008. At that point, the SSO reached oversold area and generated a buy crossover (x) (this is the one to ignore). Soon after, the SSO rose slightly, produced a sell crossover, dropped back near oversold, and then gave the second buy crossover — from above 20 (highlighted by green circle), this is the signal to act upon. The timing was exceptional (as pointed by the green arrow), as the signal appeared even before the price broke resistance or confirmed the medium-term uptrend.

Interestingly, this uptrend concluded with an SSO second sell signal, as indicated by the dotted circle in both the lower panel (SSO) and upper panel (price).

2-At the end of an upward move during uptrend:

In this case, the signal usually suggests a temporary correction to the downside within the larger uptrend. It typically appears on the lower time frame. For example, if the major trend is up on a weekly chart, this SSO second signal often shows on the daily chart. Occasionally, it may also appear on the same time frame.

Chart 13: Gold (XAU=) Daily candlestick chart along with Slow Stochastic Oscillator (9,5,3)



As shown in the daily chart above, in this example, the Second SSO signal appeared on the same time frame. Gold was moving sideways until it broke above the resistance (horizontal green line) to resume its uptrend. The SSO reached overbought area and generated the first sell crossover (X) (this is the one to ignore). Then, it provided a bullish crossover returning to the overbought area and prices achieved a new high, and then, the SSO gave the second sell signal (highlighted by green circle), this is the signal to act upon. The signal occurred right at the peak of the price move, just before the correction began, (as pointed by the red arrow).

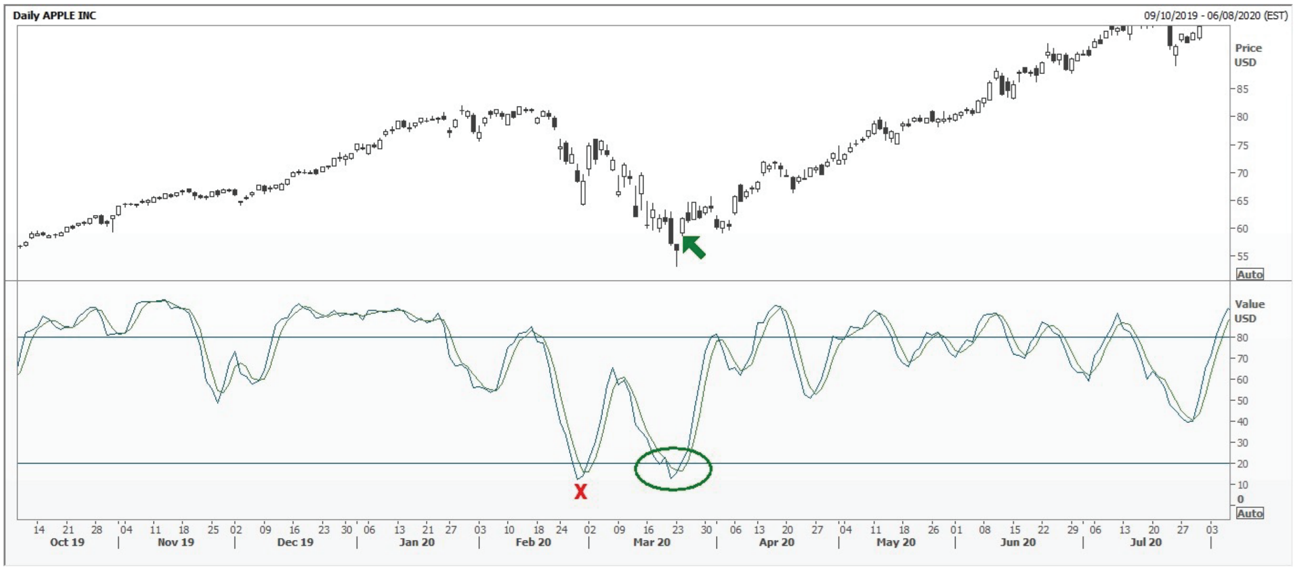
3-At the end of a downward move during uptrend:

Here, the signal suggests the end of a correction and that the uptrend will resume. It typically appears on the lower time frame, although in cases of high volatility or extended corrections, it can also appear on the same chart.

Chart 14: Apple Inc (APPL.O) Weekly candlestick chart

The chart above is showing a significant correction that APPL experienced in early 2020 within its primary uptrend (highlighted by red dots), the next chart shows the same period on the daily chart with the SSO applied.

Chart 15: Apple Inc (APPL.O) Daily candlestick chart along with Slow Stochastic Oscillator (9,5,3)

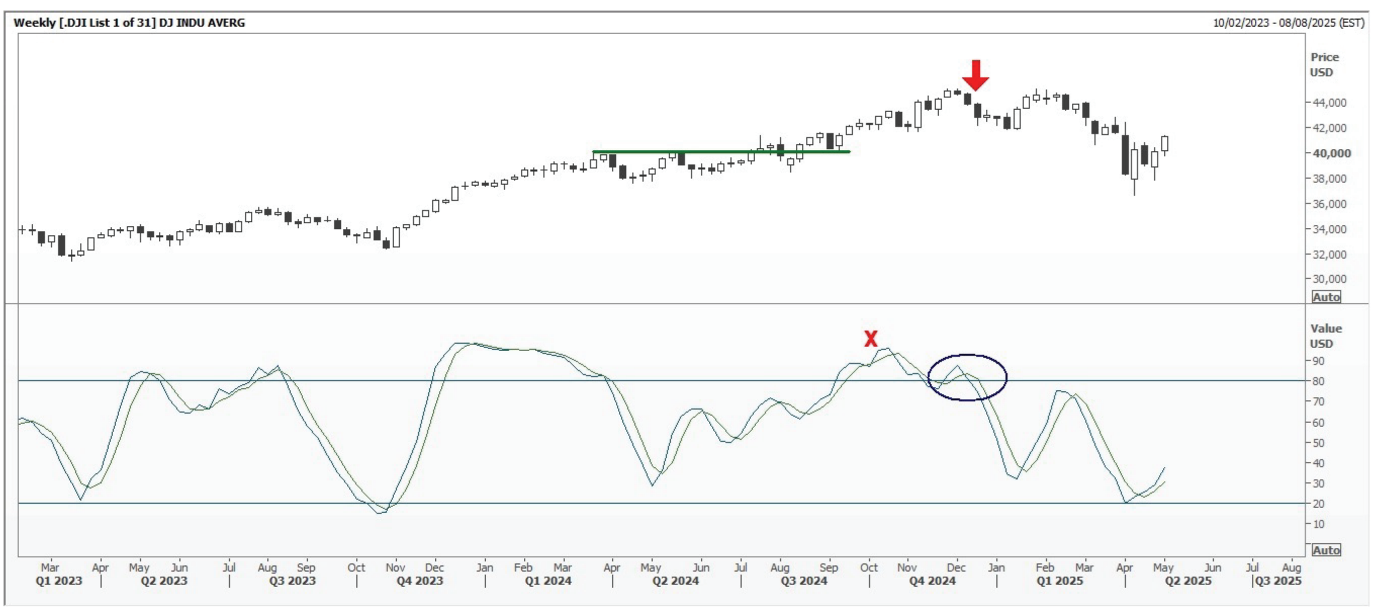


From the daily chart, we can see that the correction ended with the SSO's second buy signal. The first bullish crossover (X) had little impact on price and should be ignored. The second bullish signal (highlighted by green circle), however, marked the end of the correction. It appeared at a very early stage (as pointed by the green arrow), well before the breakout above resistance and the confirmation of the medium-term uptrend resumption.

4-At the start of a main peak:

This signal usually marks the beginning of a trend reversal to the downside. It typically appears on the same timeframe as the chart under study. Some volatility or temporary movement against the signal may occur afterward, but the signal remains valid.

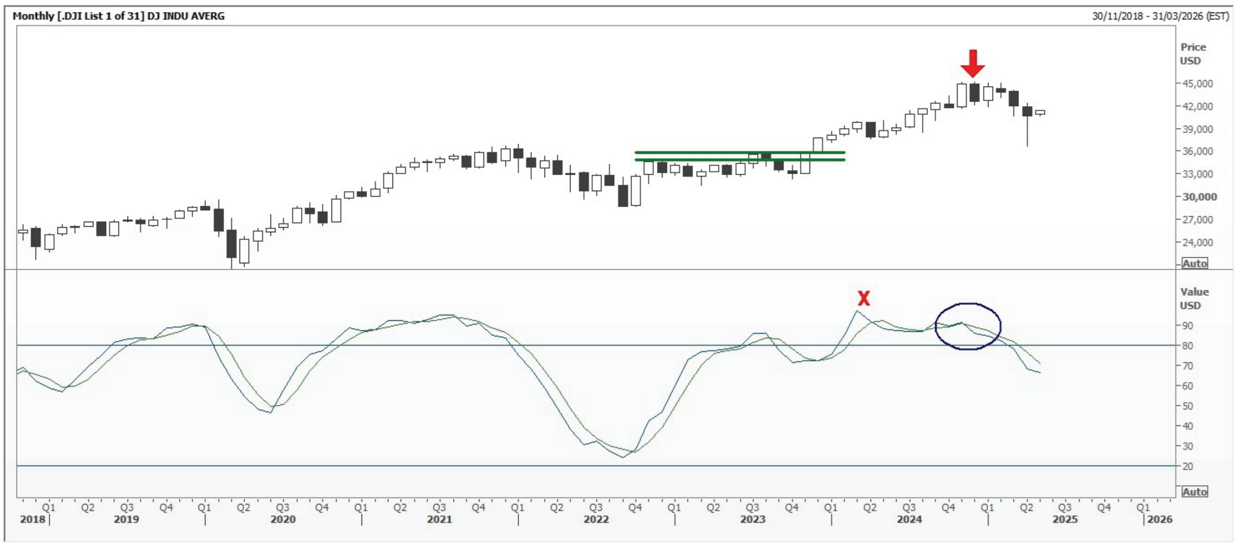
Chart 16: The Dow Jones Industrial Average (.DJI) weekly candlestick chart along with Slow Stochastic Oscillator (9,5,3)



As seen in the weekly chart of the DJI during Q2 2024, the index was moving sideways before breaking the upper boundary to the upside (horizontal green line), continuing its long-term bull trend. The SSO reached the overbought area and gave the first sell signal (X) (this should be ignored). Prices did not decline significantly after this signal. The second sell signal occurred at a higher price peak and marked the true start of the reversal (highlighted by green circle). It appeared before any confirmed breakdown and before the medium-term downtrend was clearly established (as pointed by the red arrow). As noted earlier, temporary price volatility against the signal may occur, as it did here, with prices retested the prior peak before falling.

The following monthly chart is particularly notable, as the same second sell signal appeared there simultaneously.

Chart 17: The Dow Jones Industrial Average (.DJI) Monthly candlestick chart along with Slow Stochastic Oscillator (9,5,3)



As shown in the monthly chart, the long-term bull trend resumed in Q4 2023. The SSO reached overbought area and gave the first sell signal (X) (this is the one to ignore). No significant decline followed that signal. The second sell signal (highlighted by green circle) appeared precisely at the top (as pointed by the red arrow), and a major drop began immediately afterward.

5-At the end of a downward move during downtrend:

In this case, the signal usually suggests a temporary correction to the upside within the larger downtrend. It typically appears on the lower time frame. For example, if the major trend is down on a weekly chart, this SSO second signal often shows on the daily chart. Occasionally, it may also appear on the same time frame.

Chart 18: CBoT 10 Year US Treasury Note Composite Bond Future (TYc1) Weekly candlestick chart along with Slow Stochastic Oscillator (9,5,3)

The weekly chart above shows that the 10-Year Treasury Note was in a bearish trend. In Q2 2023, an upward correction ended with a breakdown below support level (horizontal red line). The SSO reached oversold area and gave the first buy signal (X) (this one should be ignored), where no significant rise followed that signal. The second buy signal (highlighted by green circle), however, occurred exactly at the bottom (as pointed by the green arrow), and followed by a strong upward correction.

6-In the end of an upward move during downtrend:

Here, the signal suggests the end of a correction and that the downtrend will resume. It typically appears on the lower time frame, although in cases of high volatility or extended corrections, it can also appear on the same chart.

Chart 19: Hang Seng Index (.HSI) – Hong Kong – Weekly candlestick chart

As seen in the weekly chart above, the market witnessed a notable upward correction against its prevailing downtrend in Q4 2022 (highlighted with red dots). The next chart shows this period on the daily chart with SSO applied.

Chart 20: Hang Seng Index (.HSI) – Hong Kong – Daily candlestick chart along with Slow Stochastic Oscillator (9,5,3)

The daily chart above shows that the upward correction ended with the SSO second sell signal. The first bearish crossover (X) had minimal impact on price. The second signal (highlighted by green circle), however, clearly marked the end of the correction. It appeared early (as pointed by the red arrow), before the breakdown below support and prior to confirmation of the medium-term downtrend resumption.

Note: One might count the first sell signal that appeared just after the trend reversal, but I deliberately excluded it because it coincided with the breakout. I only began counting signals afterward. However, even if that earlier crossover were counted as the first signal, and that the second signal is the one marked with "X", still closely coincided with the correction's end.

5. Time Cycles and the Stochastic Oscillator Second Signal Enhancement

As discussed earlier in Section 3 - particularly in the third point - the strength or reliability of technical indicators signals (including buy/sell or strength/weakness signals) is often the result of the interaction of multiple time cycles within a stock or market. The summation of these cycles - differing in both period and direction - produces what we refer to as the ripples effect and accordingly produces the technical indicators signals.

In this context, the SSO second signals outlined in the previous section were not just technically accurate, they also coincided with moments when different time cycles collided. This collision is what gave those signals their exceptional predictive power.

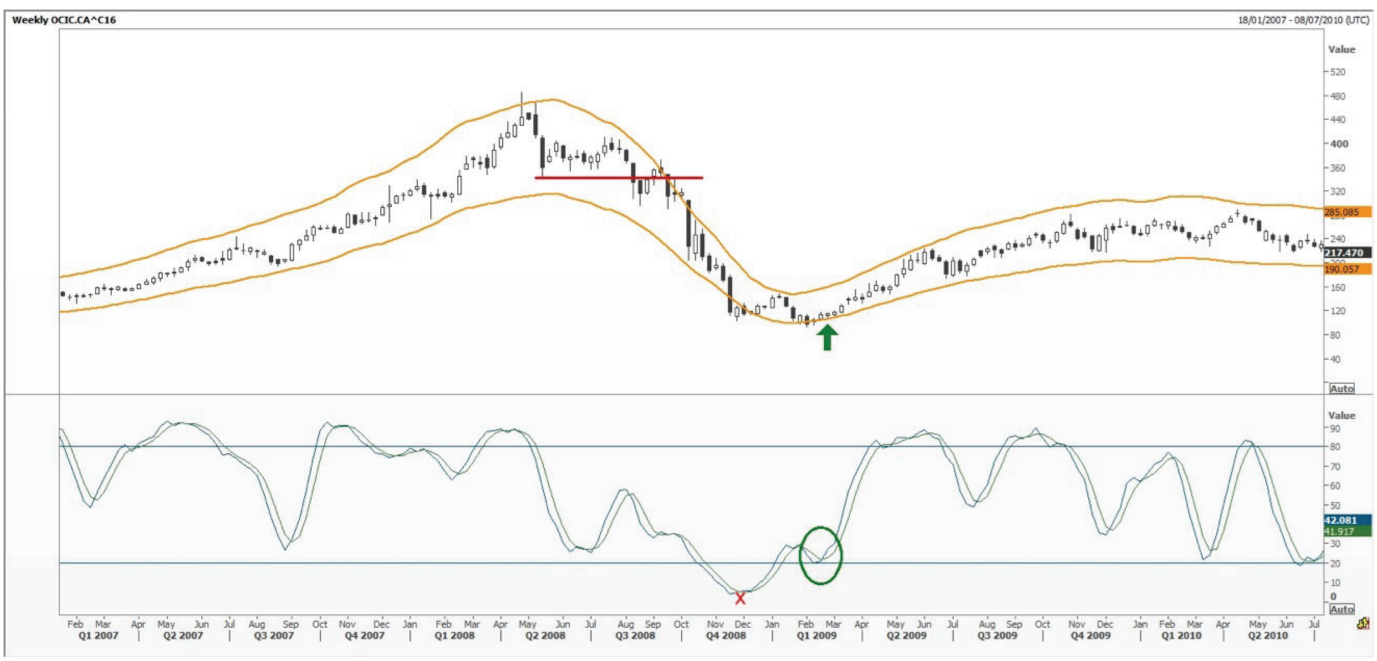
As a result, integrating cycles analysis or using envelopes to visualize the different time cycles (14) will enhance or confirm SSO second signals.

The following charts revisit the same case studies from section 4.2.2, but this time, each chart includes centered envelopes, allowing us to visually identify how the SSO second signals align with key cycle bottom/top or the collision of different cycles.

1. At the start of a main bottom:

In this case, as shown in the chart below, the second SSO signal appeared exactly at the trough of a major 3.5–4 year cycle (at the lower boundary of the orange channel that is shifting its direction from down to up), confirming the beginning of a new bullish direction. This alignment between the cycle low and the second bullish crossover significantly enhanced the reliability and strength of the signal.

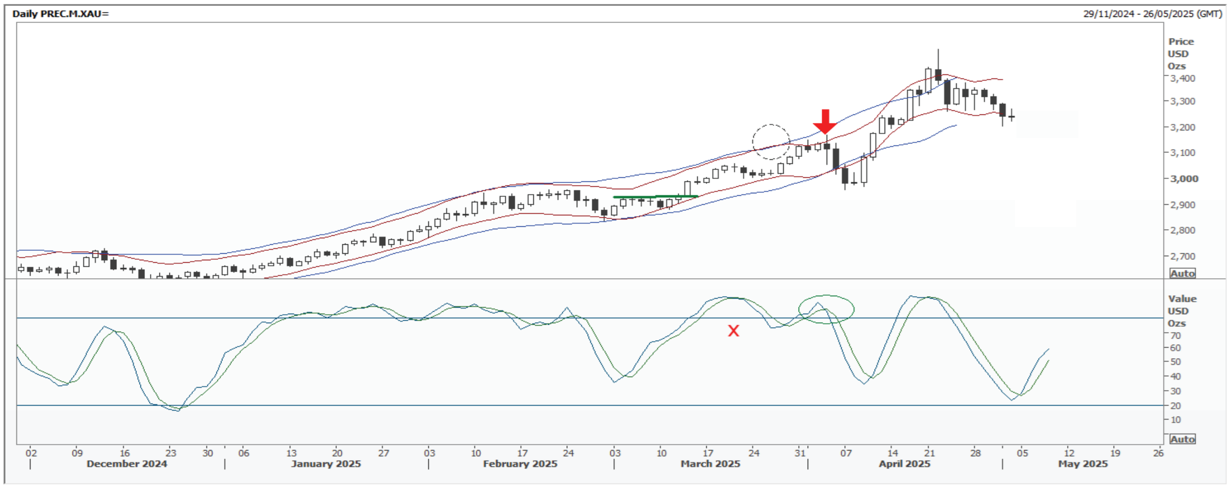
Chart 21: Orascom Construction (OCIC.CA) - the Egyptian Stock market - Weekly candlestick chart along with 20 Week Centered envelopes with 20-20% margins (orange channel) and Slow Stochastic Oscillator (9,5,3)



2. At the end of an upward move during uptrend:

In this case, as shown in the chart below, the second SSO signal coincided with the crest of a short-term 20 days cycle and its interaction with the upper boundary of a relatively rising long-term 40 days cycle (highlighted by dotted circle). The timing of this signal, confirmed the alignment of both the short and long cycles, marked the start of a downward correction within the ongoing uptrend. This multi-cycle interaction validated the SSO signal and gave it more weight in anticipating the price decline.

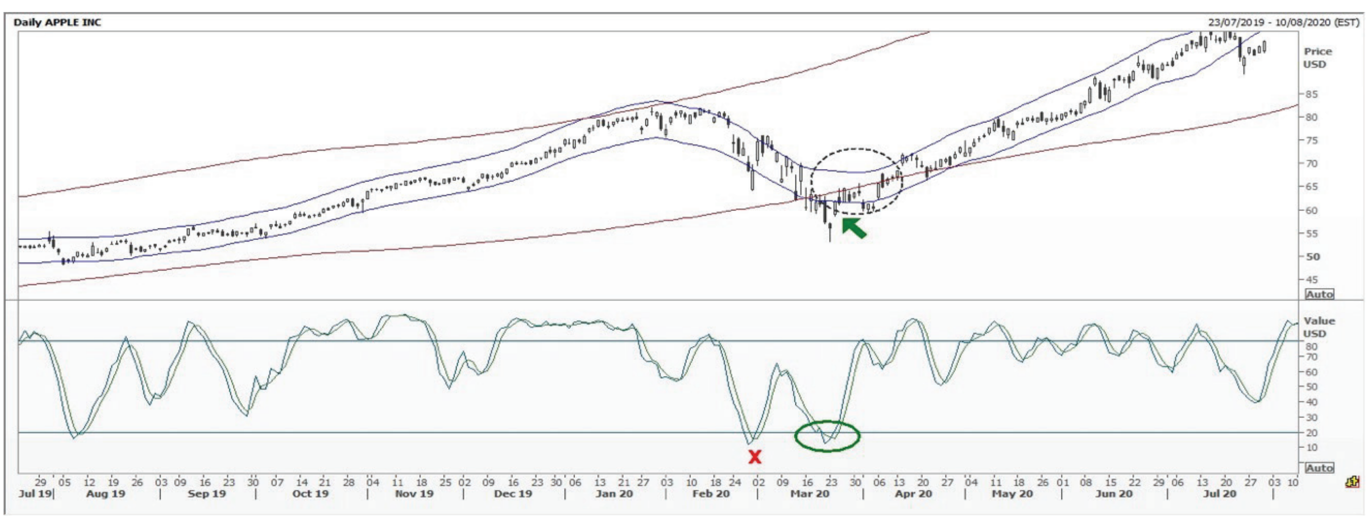
Chart 22: Gold (XAU=) Daily candlestick chart along with 20 Days Centered envelopes with 2.5-3% margins (blue channel) and 10 Days Centered envelopes with 2-2% margins (Dark red channel) and Slow Stochastic Oscillator (9,5,3)



3. In the end of a downward move during uptrend:

In this case, as show in the chart below, the second SSO signal appeared as the short-term cycle bottomed after hitting the lower boundary of the long-term rising cycle (highlighted by dotted circle). This multi-cycle collision validated the SSO signal and marked the end of the downward correction.

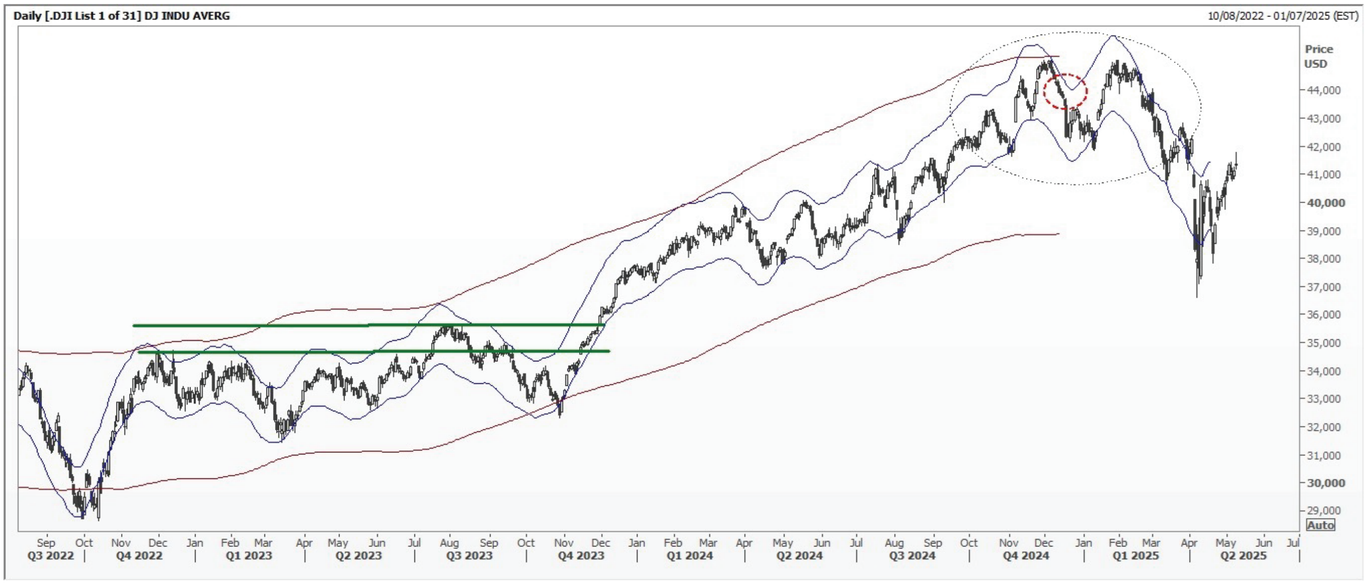
Chart 23: Apple Inc (APPL.O) Daily candlestick chart along with 200 Days Centered envelopes with 18-18% margins (Dark red channel) and 30 Days Centered envelopes with 5-5% margins (blue channel) and Slow Stochastic Oscillator (9,5,3)



4. At the start of a main Peak:

The chart below is the daily version of charts 16 and 17, but this time it incorporates envelope channels of different time spans to illustrate the interplay of multiple time cycles on a single chart. It clearly demonstrates the summation principle; where the relative long-term cycle was peaking and acted as a barrier, preventing the relative short-term cycle from pushing the prices to new highs. The SSO second signal was perfectly provided at the beginning of this confluence, as marked by the red dotted circle.

Chart 24: The Dow Jones Industrial Average (.DJI) Daily candlestick chart along with 200 Days Centered envelopes with 7-8% margins (Dark red channel) and 20 Days Centered envelopes with 3-3% margins (blue channel)

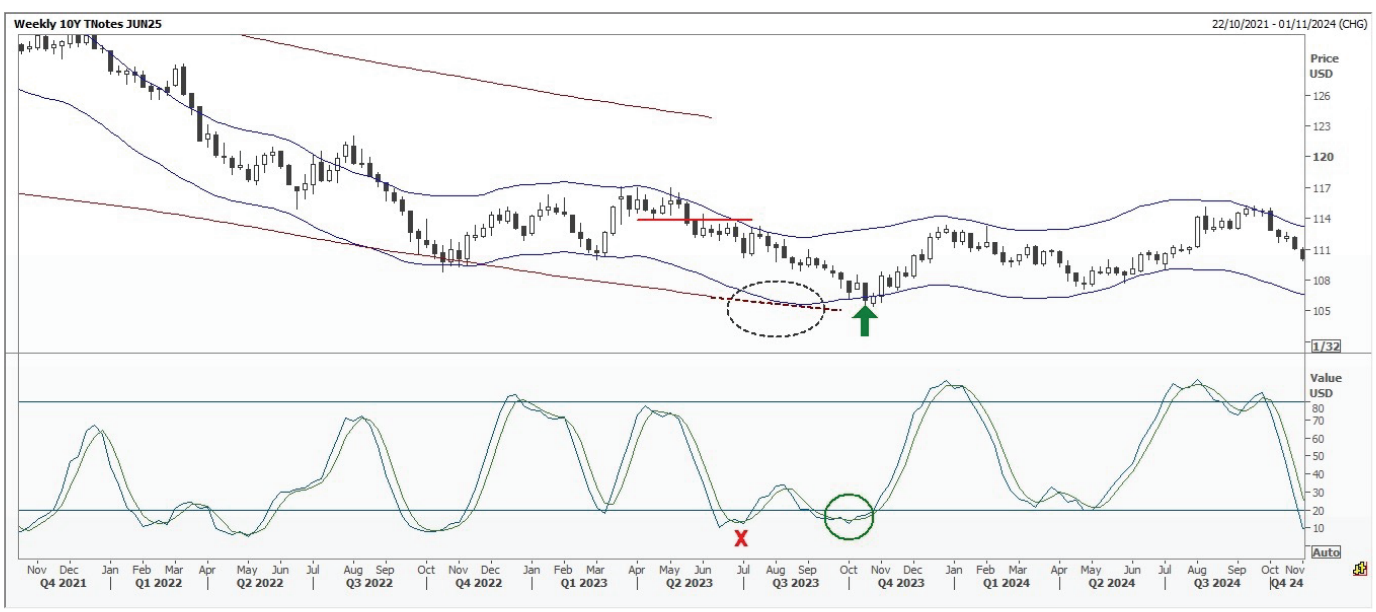


5. At the end of a downward move during downtrend:

In this case, as shown in the chart below, the second SSO signal coincided with the trough of a relatively short-term cycle (40-44 week cycle) and its interaction with the lower boundary of a relatively falling long-term cycle (300-310 week cycle) (marked with a dotted circle). This multi-cycle interaction validated the SSO signal and gave it more weight in anticipating the price rise. The signal was provided just as prices started to rise, marking the beginning of a notable upward correction.

It is important to note that, since the envelopes are centered, the lower boundary has been extended with a dotted line to clearly highlight the point of intersection.

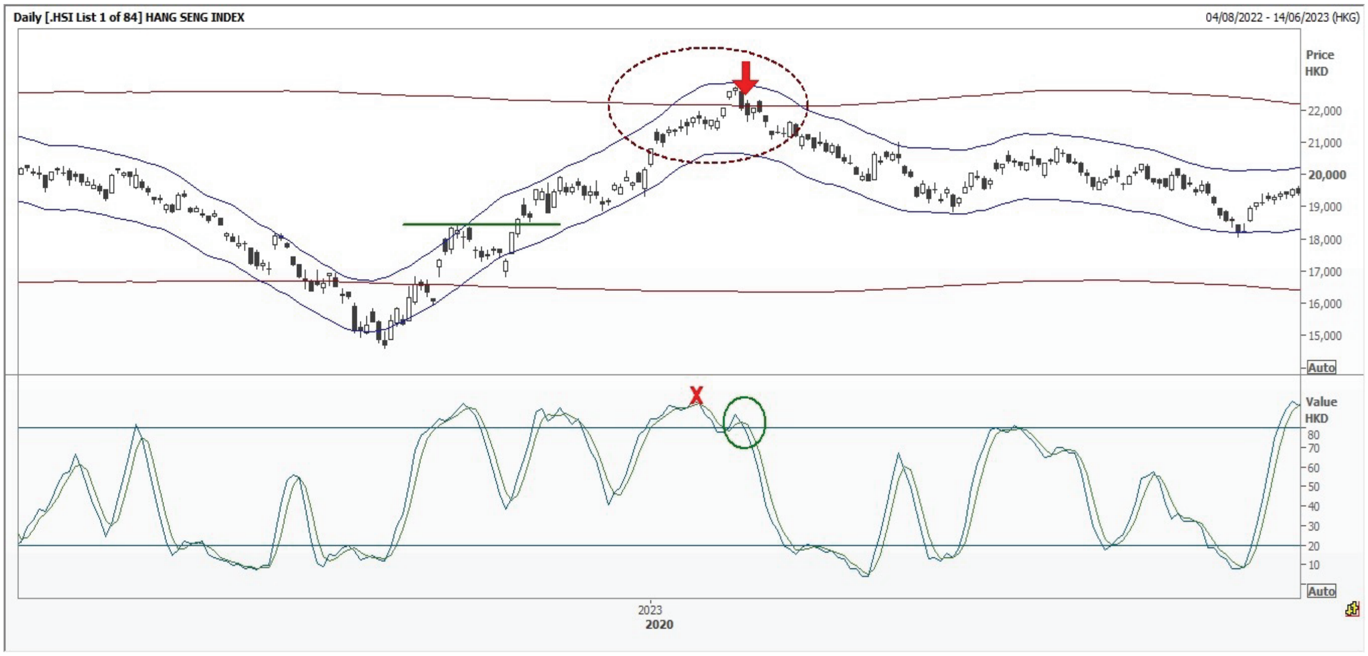
Chart 25: CBoT 10 Year US Treasury Note Composite Bond Future (TYc1) Weekly candlestick chart along with 200 Weeks Centered envelopes with 7-8% margins (Dark red channel) and 20 Weeks Centered envelopes with 3-3% margins (blue channel) and Slow Stochastic Oscillator (9,5,3)



6. At the end of an upward move during downtrend:

The chart below shows how the signal was provided when the relative short-term cycle reached its peak and collided with the upper boundary of the falling long-term cycle (highlighted by dotted circle), initiating a new decline within the broader downtrend. The timing of the second SSO sell signal coincided with this cyclical convergence, enhancing its reliability and significance.

Chart 26: Hang Seng Index (.HSI) - Hong Kong - Daily candlestick chart along with 200 Days Centered envelopes with 15-15% margins (Dark red channel) and 20 Days Centered envelopes with 5-5% margins (blue channel) and Slow Stochastic Oscillator (9,5,3)



5.1 Time cycles and the Stochastic Oscillator Second Signal justification

The previous section and its examples demonstrated where the second signals occurred, and how applying time cycles or centered envelopes served to enhance and confirm those signals.

This section aims to explore, in depth, the rationale behind the success of the second signal in the Slow Stochastic Oscillator (SSO) compared to the earlier crossover signal. The answer appears to lie in the principles of Summation, Harmonicity, and, in certain cases, Synchronicity.

First let us revisit these principles as presented in John J. Murphy's book *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications* (15) and demonstrate a conceptual framework of how they interact to produce such signals:

The principle of Summation holds that all price movement is the simple addition of all active cycles. The Harmonicity simply means that neighboring waves are usually related by a small, whole number. Finally, the Synchronicity principle which refer to the strong tendency for waves of differing lengths to bottom at about the same time.

Based on these principles, every directional move in the market, or any shift in direction, is the result of the combined effect of one or more of these principles.

The different scenarios that gave rise to the successful second SSO signals are demonstrated below:

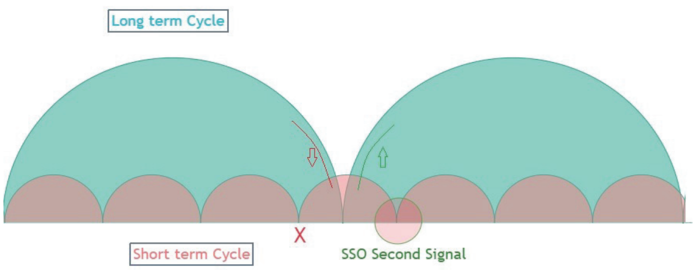
1. At the start of a main bottom:

Figure 3 below illustrates the interaction between a long-term cycle and a relatively short-term cycle. According to the summation and harmonicity principles, the decline (right) side of the long-term cycle typically includes smaller cycle that is repeated one or two times.

This explains the failure of the first SSO buy signal, as it is triggered by the rising phase of the short-term cycle while the longer-term cycle is still in decline (X). On the other hand, the SSO second signal carries far more significance, as it usually occurs when both the short-term and long-term cycles are rising together. Notably, this signal tends to appear early in the new uptrend since it forms at the end of the falling short-term cycle (highlighted by green circle).

Note: This simplified illustration uses only two cycles for clarity. In reality, at a major market bottom, multiple cycles of different durations are usually bottoming simultaneously (synchronicity).

Figure 3: Conceptual illustration of a bottom created by a long-term cycle (blue) and a short-term cycle (Red)

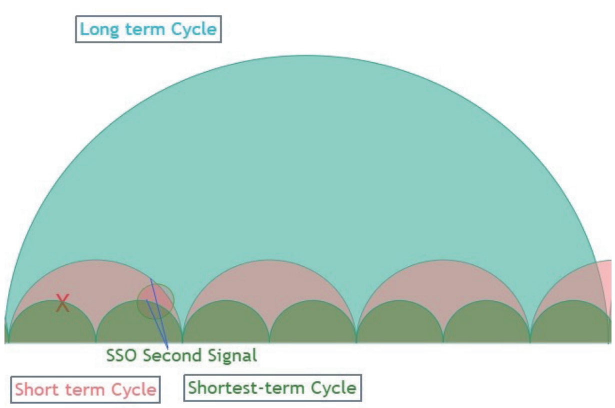


2. At the end of an upward move during uptrend:

According to Figure 4 below, an uptrend is defined by a rising long-term cycle (the left side of the blue cycle). For the price to slow down and enter a correction, the other short-term cycles must be falling. When the SSO provided the first sell signal, it will not be effective because it is triggered by the declining shortest-term cycle, while both the short-term and long-term cycles are still rising (X).

In contrast, the SSO second sell signal tend to be successful, at this point, both the short-term and shortest-term cycles have begun to decline (highlighted by green circle), initiating the expected downward correction.

Figure 4: Conceptual illustration of the start of a correction during an uptrend by a long-term cycle (blue), a short-term cycle (red), and a shortest-term cycle (green)

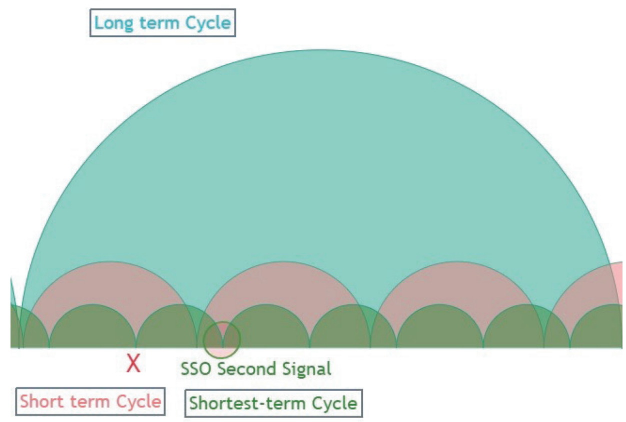


3. At the end of a downward move during uptrend:

As previously mentioned, and as shown in Figure 5 below, an uptrend is defined by a rising long-term cycle (the left side of the blue cycle). At the end of a downward correction, the two shorter-term cycles are typically nearing the end of their falling phases. These cycles will then begin to rise, either together or successively. When the SSO provided the first buy signal it will not be effective, as it is triggered by the rising shortest-term cycle while the short-term cycle is still declining (X).

In contrast, the SSO second buy signal tends to be successful as both the short-term and the shortest-term cycles have begun to rise (highlighted by green circle), allowing the price to resume its upward movement. In this case, the Synchronicity principle plays an important role, where the more the shortest-term cycle and the short-term cycle are synchronized, the more is the strength and significance of the following move.

Figure 5: Conceptual illustration of a correction termination during an uptrend by a long-term cycle (blue), a short-term Cycle (Red) and the shortest-term cycle (green)

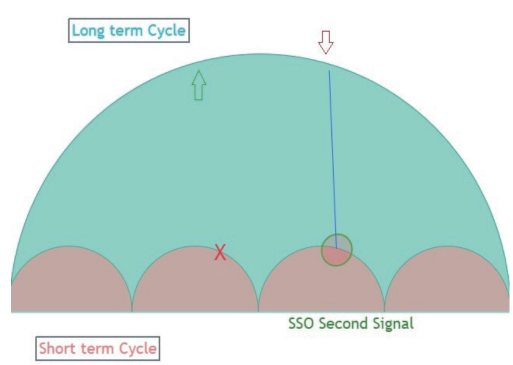


4. At the start of a main Peak:

Figure 6 below illustrates a long-term cycle and a relatively short-term cycle. According to the principles of summation and harmonicity, during the left side (the rising phase) of the long-term cycle, any sell signal generated by the short-term cycle typically indicates only a correction, not a major top. This explains why the first SSO sell signal (X) tends to fail, as it is triggered by the falling short-term cycle while the long-term cycle is still rising. In contrast, the SSO second sell signal becomes significant, as it is generated when both the long-term and short-term cycles have started to decline (highlighted by green circle).

Note: This two-cycle illustration is simplified for clarity. In actual market conditions, a main peak often forms when multiple cycles are peaking simultaneously. Additionally, any shortest-term cycles still rising into the peak can contribute to generating the sell signal at a relatively high price level.

Figure 6: Conceptual illustration of a peak created by a long-term cycle (blue) and a short-term Cycle (Red)



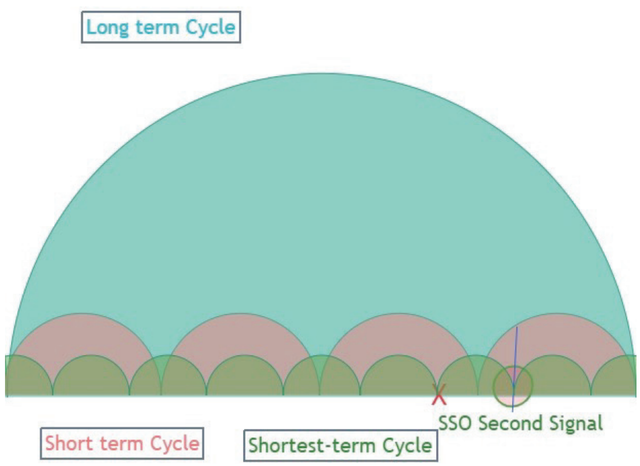
5. At the end of a downward move during downtrend:

According to Figure 7 below, a downtrend is defined by a falling long-term cycle (the right side of the blue cycle). At the end of a downward move, in order for the price to slow down the decline and witness an upside correction, the other two shorter-term cycles will be near the end of their declining phase. These cycles will then begin to rise—either together or successively.

When the SSO provides the first buy signal, it will not be effective as it is triggered by the rising shortest-term cycle while the short-term and long-term cycles are still falling (X), In contrast, the SSO second buy signal tends to be successful, as both the short-term and the shortest-term cycles have begun to rise (highlighted by green circle), allowing the price to experience a corrective upward move.

In this case, the Synchronicity principle plays an important role, where the more the shortest-term cycle and the short-term cycle are synchronized, the more is the strength and significance of the following move.

Figure 7: Conceptual illustration of the start of an upward correction during a downtrend by a long-term cycle (blue), a short-term Cycle (Red) and the shortest-term cycle (green)

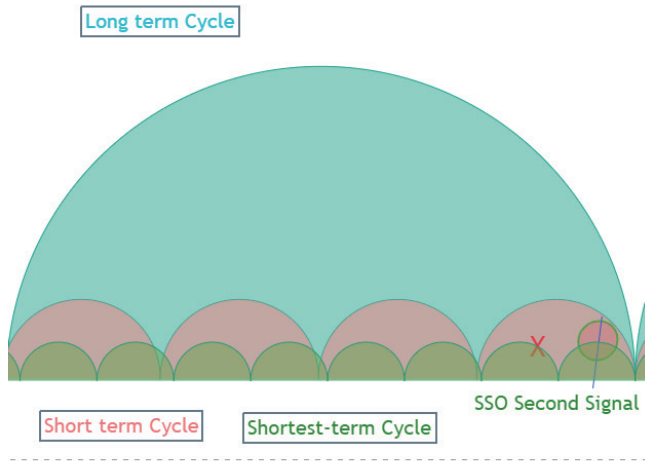


6. At the end of an upward move during downtrend:

As shown in Figure 8 below, a downtrend is defined by a falling long-term cycle (the right side of the blue cycle). At the end of an upward correction, the two shorter-term cycles are typically nearing the end of their rising phases. These cycles will then begin to fall, either together or successively.

When the SSO provided the first sell signal it will not be effective, as it is triggered by the falling shortest-term cycle while the short-term cycle is still rising (X). In contrast, the SSO second sell signal tends to be successful as both the short-term and the shortest-term cycles have begun to decline (highlighted by green circle), allowing the price to resume its downward movement.

Figure 8: Conceptual illustration of a correction termination during a downtrend by a long-term cycle (blue), a short-term Cycle (Red) and the shortest-term cycle (green)



After illustrating the various scenarios that lead to successful SSO second signals, driven by the interaction of different time cycles and their underlying principles, there is yet another important principle that can enhance our understanding of the SSO second signal. While it does not explain the signal's success, it offers insight into its potential magnitude. This is the principle of proportionality, which states: "Cycles with longer periods (lengths) should have proportionally wider amplitudes". (16) Accordingly, the following key points should be considered:

1. The long-term cycle is the most important cycle to monitor. It serves as the dominant force and provides guidance regarding the potential magnitude of the move.
2. A strong upside potential following the second SSO signal is most likely in cases of a market bottom or the end of a downward correction during an uptrend (in other words, when the long-term cycle starts to rise or is already rising).
3. A strong downside potential following the second SSO signal is most likely in cases of a market top or the end of an upward correction (in other words, when the long-term cycle starts to fall or is already falling).
4. A smaller magnitude move is expected following the second SSO signal in cases of the end of an upward move during an uptrend or the end of a downward move during a downtrend (in other words, the start of a correction that will be moving against the dominant long-term cycle).
5. It is always recommended to use a higher degree (long-term) chart when analyzing the second SSO signals that occur in the formation of main bottoms or peaks.
6. It is always recommended to use a smaller degree (short-term) chart when analyzing the second SSO signals that occur at the beginning or end of corrections.

6. Conclusion

Dealing with the market is not an easy task. Price behavior is difficult to predict. Despite its trending nature, it still contains a degree of randomness. As a result, signals generated by various technical Analysis indicators will also include some level of randomness and occasional failure. This characteristic of the market is well explained by the concept of summation in time cycles. Therefore, when analyzing price action, it is essential to consider time analysis alongside the chosen technical analysis indicator(s), or even when interpreting signals from price action itself.

In this article, a special signal was introduced, one provided by the Slow Stochastic Oscillator (9, 5, 3), widely regarded as one of the best Technical Analysis indicators for generating crossovers with each price movement.

The introduced signal is called the SSO second signal. Its importance lies in the fact that its failure is rare, particularly when the recommended steps are followed before identifying or acting on it.

In case of an uptrend:

1. The price is trending upward, confirmed by a break above previous peak.
2. The SSO reaches overbought area and provides a sell crossover signal. (It is preferable if it declines below 80 level, but this is not a strict requirement, and it should not reach oversold area). At this stage, the subsequent price movement is usually insignificant.
3. The SSO provides a buy crossover again and attempts to reach overbought area once more. Most of the time, this is accompanied by a new high in the price.
4. The SSO then provides the second sell crossover signal from the overbought area (whether above 80 level or slightly below 80 level is acceptable). This is the signal we should act upon by selling the asset under study.
5. The re-entry level (to cover the short or re-buy) should be set above the last price peak that corresponds to the SSO's second sell crossover.

In case of downtrend:

1. The price is trending downward, confirmed by a break below previous bottom.
2. The SSO reaches oversold area and provides a buy crossover signal. (It is preferable if it rises above 20 level, but this is not a strict requirement, and it should not reach overbought area). At this stage, the subsequent price movement is usually insignificant.
3. The SSO provides a sell crossover again and attempts to reach oversold area once more. Most of the time, this is accompanied by a new low in the price.
4. The SSO then provides the second buy crossover signal from the oversold area (either below 20 level or slightly above it). This is the signal we should act upon by buying the asset under study.
5. The stop-loss level should be placed below the last price bottom that corresponds to the SSO's second buy crossover.

The SSO second signal can be seen in different market situations:

1. At the start of a main bottom
2. At the end of an upward move during uptrend
3. At the end of a downward move during uptrend
4. At the start of a main Peak
5. At the end of a downward move during downtrend
6. At the end of an upward move during downtrend

It is clear, that, the success of this signal is strongly supported and justified by time cycles, which—as discussed—are a vital component when dealing with the market. Even if time cycle analysis is not actively used as a parallel tool, the signal itself serves as a reflection of time-cycle market behavior. However, applying this signal in combination with time analysis will further enhance and validate it, offering greater insight into the expected magnitude of the resulting price movement.

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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 (Part II)

Davide Pandini, Ph.D., MFTA, CFTe, CMT, CSTA*
***Certified SIAT Technical Analyst – SIAT (Società Italiana Analisi Tecnica)**

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

Foreword

In the ever-evolving landscape of financial markets, accurately and reliably forecasting asset prices and market trends remains a critical challenge for analysts, traders, and investors. This comprehensive essay, divided into four parts, presents a detailed exploration of statistical forecasting methods, rigorously evaluating their effectiveness and comparative advantages in the financial sector. In the initial part of this essay, published in the IFTA 2025 Journal, readers were introduced to the fundamental concepts of financial forecasting. This included a general introduction to forecasting models and their components, a detailed description of the financial asset and time series data, segmentation of the historical backtesting period into training and testing ranges, and essential discussions on model selection criteria and forecasting accuracy metrics. Furthermore, the 2025 issue provided a comprehensive analysis of simple forecasting methods—arithmetic mean, random walk, seasonal random walk, and random walk with drift—establishing a necessary foundation for understanding more complex forecasting models.

To effectively transition to more advanced methods, the current IFTA 2026 issue builds directly upon the previous insights by analyzing in detail the exponential smoothing techniques. Exponential smoothing methods are particularly suited for capturing dynamic market conditions and rapidly changing trends, providing a natural progression from the simpler models previously examined. Recognized for their robustness and adaptability in short- to medium-term market forecasting, exponential smoothing techniques efficiently adapt to new market information by assigning exponentially decreasing weights to historical data. This paper extensively explores methods including the baseline Simple Moving Average, Brown's Simple Exponential Smoothing, Holt Linear Trend, Exponential Trend, Gardner Additive Damped Trend, Taylor Multiplicative Damped Trend, Holt-Winters Additive, Holt-Winters Multiplicative, and Holt-Winters Damped methods. Detailed procedures for optimal parameter selection, model validation, and thorough evaluations using information loss criteria and forecasting accuracy metrics are also discussed. One of the key objectives is to provide the financial community with a comprehensive and rigorously assessed collection of forecasting techniques, enabling better-informed decisions. By carefully evaluating each exponential smoothing method's strengths and limitations, this work ensures that readers can select the most appropriate forecasting approach tailored to specific market conditions, enhancing their strategic decision-making capabilities.

Looking ahead, readers are encouraged to stay tuned for subsequent issues of the IFTA Journal. Future publications will offer comprehensive insights into ARIMA (AutoRegressive Integrated Moving Average) models and their variants, including non-seasonal and seasonal ARIMA models, detailed methodologies for stationarity testing, and model optimization procedures. Furthermore, advanced forecasting methods will be addressed through GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) models, including ARIMA-GARCH hybrid approaches, which tackle the complexities of financial market volatility and non-Gaussian data characteristics.

By means of this structured approach, traders, analysts, and investors can gain incremental and thorough knowledge of statistical forecasting, building from foundational methods to sophisticated analytical techniques, providing a clear, strategic roadmap for mastering market prediction within the realm of Financial Technical Analysis.

1. Introduction

Financial time series forecasting is a core challenge in both research and practice, with accurate predictions playing a crucial role in investment strategy, risk management, trading decisions, and economic planning. However, the inherently volatile and often near-random-walk nature of financial markets [24] makes forecasting a very difficult task. A wide range of forecasting techniques have been developed to tackle this problem. Traditional statistical models, represented by the Box-Jenkins AutoRegressive Integrated Moving Average (ARIMA) methodology [6][7][23], have long been used to capture autocorrelations in time series data. More recently, machine learning and artificial intelligence approaches (including neural networks and other "intelligent" models) have been considered for financial forecasting [8], aiming to handle nonlinear patterns and large data sets. Despite the emergence of these advanced approaches, simpler time series methods remain highly relevant [9]. In particular, exponential smoothing techniques are still considered as indispensable tools, for their robustness, transparency, and forecasting accuracy. This paper focuses on exponential smoothing methods for financial forecasting, examining their performance and highlighting their role in the domain of technical and quantitative analysis.

Exponential smoothing (ES) encompasses a set of forecasting methodologies that generate predictions by assigning exponentially diminishing weights to historical data points. By assigning greater weight to the most recent observations, exponential smoothing is able to sensitively adjust to shifts in the level, trend, or seasonality of a time series. The simplest form, single exponential smoothing, is designed for series without pronounced trend or seasonality and effectively computes a recursively weighted moving average. More advanced variants, such as Holt's linear double exponential smoothing for trended data and the Holt-Winters triple exponential smoothing for seasonal data, extend the basic approach to capture more complex patterns. These methods are defined by a small number of smoothing parameters (for level, trend, and seasonality) that determine the rate at which the influence of older observations decays. The practical relevance of exponential smoothing lies in its conceptual simplicity and computational efficiency, combined with empirically solid performance across many domains including finance. For instance, exponential smoothing is used by financial analysts to filter noise from asset price series and to forecast future values of economic indicators, often providing competitive results with minimal model complexity.

Exponential smoothing were first introduced in the late 1950s and early 1960s by pioneers such as Holt, Winters, and Brown [17][18][19][22][26]. These methods were initially developed to improve inventory control forecasts and to project trends in economic data. Holt's seminal work (1957) [18] proposed a method for exponentially smoothing data with a linear trend, later known as Holt's two-parameter method. Winters (1960) [22] further extended the approach to address seasonality, formulating what is now referred to as the Holt-Winters seasonal smoothing method. Over time, refinements such as the damped trend method were introduced to moderate long-term trend extrapolation, with Gardner and McKenzie (1985) [20] showing that adding a damping parameter often improves forecast accuracy by preventing unrealistically explosive trend forecasts. By the mid-1980s, exponential smoothing had been firmly established as a mainstream forecasting approach, bolstered by Gardner's influential 1985 review [27] that rigorously analyzed its variants and performance. In the subsequent decades, these methods have been applied to several problems across various fields and have been included in virtually all major forecasting software and textbooks as fundamental tools.

Moreover, exponential smoothing techniques have also demonstrated strong empirical performance. Notably, exponential smoothing has repeatedly excelled in large-scale forecasting competitions. For example, in the influential Makridakis competitions [1][2][3][4], relatively simple methods like Holt-Winters smoothing often performed on par with or better than more complex models. Such outcomes have led to exponential smoothing being regarded as one of the benchmarks for forecast accuracy. Surveys of forecasting practice also underscore its prominence — Weller and Crone (2012) [30] report that exponential smoothing was the most frequently used forecasting method by industry practitioners, employed in roughly 32% of cases. This enduring success is attributed to the method's ability to adapt to a wide range of time series patterns with only a few parameters, thereby achieving a favorable balance between bias and variance. In fact, the damped trend variant of exponential smoothing has been described as "a benchmark forecasting method for all others to beat", having proven notoriously difficult to outperform consistently in empirical studies. These studies reinforce the credibility of exponential smoothing as a reliable forecasting approach, one that often sets a high bar for accuracy against which newer methods are compared.

A central focus of this work is the optimization of smoothing parameters using the Excel GRG (Generalized Reduced Gradient) nonlinear solver, which minimizes the sum of squared residuals within the training range. This paper critically examines the trade-offs between model complexity and forecasting accuracy, employing information loss criteria (AIC, BIC) [14][15][16] and accuracy metrics (RMSE, MAPE) [11] to guide method selection. Furthermore, the limitations of exponential smoothing—such as sensitivity to initialization, challenges in handling noisy data, and inadequacy for long-term forecasts—are explicitly addressed to provide practitioners with a balanced perspective. By emphasizing interpretability, computational efficiency, and empirical validation, and through systematic testing across training and testing ranges, the paper delivers insights into selecting and fine-tuning these models, ensuring they align with the temporal dynamics and volatility inherent in asset price forecasting.

From a theoretical standpoint, exponential smoothing methods are closely related to other time series models. Research has shown that many exponential smoothing formulations have equivalent or near-equivalent forms in the ARIMA models. For instance, simple exponential smoothing with appropriate parameters corresponds to an ARIMA(0,1,1) model with no constant, while Holt's linear method can be seen as akin to an ARIMA(0,2,2) under certain conditions. These links, first elucidated by scholars such as Muth (1960) [28] and Nerlove and Wage (1964) [29], reveal that exponential smoothing is not merely an ad-hoc heuristic, but can be derived from well-defined statistical models in the state-space or ARIMA frameworks. Contemporary developments have further placed exponential smoothing in a state-space modeling context (e.g., the ETS models of Hyndman et al., 2008 [5]), enabling probabilistic forecasts and model selection via information criteria similarly to ARIMA. Thus, exponential smoothing methods occupy a unique intersection of practicality and theoretical soundness — they are easy to use and explain, yet supported by rigorous statistical theory.

Our study reviews exponential smoothing techniques as a relevant yet relatively underappreciated approach in financial forecasting scenarios, especially compared to the heavy emphasis often placed on ARIMA and machine learning models in recent literature. We aim to evaluate and illustrate how various exponential smoothing models and damped trend variants can be effectively applied to forecast financial time series, and how their performance compares to other forecasting methods, thus offering practical insights for analysts, traders, and investors. The remainder of the paper is organized as follows. First, we describe the methodological framework, detailing the exponential smoothing models and comparative techniques, including the historical time series data used in this work. This is followed by an empirical evaluation on representative financial time series data, where forecast accuracy and model behavior are analyzed. Finally, we discuss the results in the context of financial forecasting and technical and quantitative analysis and conclude with implications and suggestions for future work.

2. Forecasting Models Data

The forecasting models' data used in this study 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 time series was downloaded from *Yahoo! Finance* [10]. 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.

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 1 and Figure 2 respectively. This historical data series is the same as in the IFTA 2025 Journal work [25].

Figure 1. SPY ETF training range (Dec 01, 2004 — Jul 09, 2018)

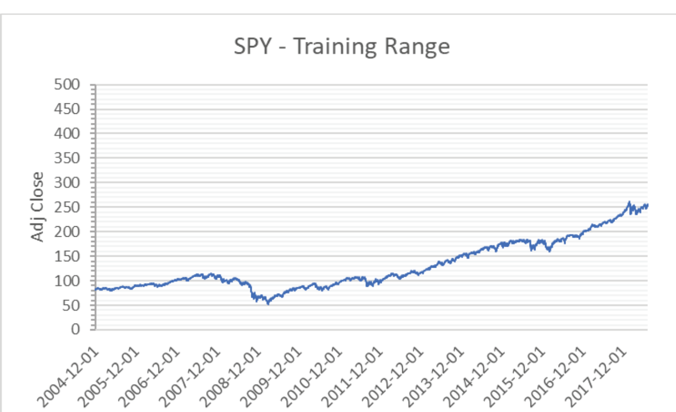
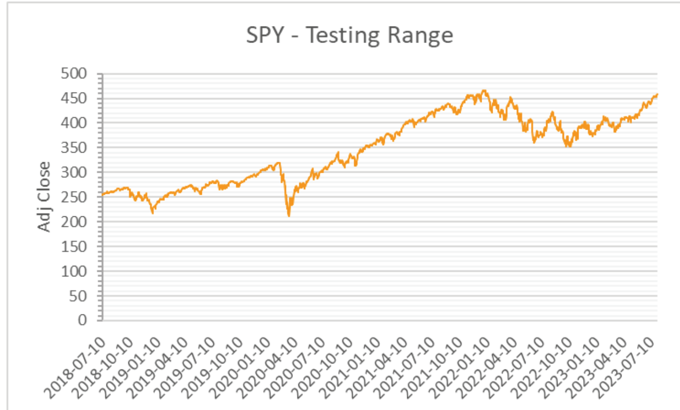


Figure 2. SPY ETF testing range (Jul 10, 2018 — Jul 31, 2023)



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 [12] 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 [13] 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 [13] 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.

3. Exponential Smoothing Methods

Exponential smoothing methods are a class of time series forecasting techniques that emphasize recent observations while assigning decreasing weights to older data points. This intrinsic characteristic allows these methods to adapt to changes in the underlying patterns, making them suitable for short-term forecasting. In this Section, we will discuss the process of parameter estimation and model selection within the exponential smoothing framework. Each exponential smoothing model comes with its own set of parameters that shape the model's behavior. Therefore, understanding how to choose and optimize these parameters is essential for achieving accurate forecasts. We will explore techniques for parameter tuning and optimization in the training range, and subsequently we will evaluate and validate the parameters' effectiveness in the testing range data set. The exponential smoothing methods evaluated in this Section are:

- Simple moving averages: These methods consist of forecasts based on previous periods data with equal weighted influence;
- Weighted moving averages: These methods consist of forecasts based on previous periods data with linearly decaying influence when they become older;
- Exponential moving averages or exponentially weighted moving averages: These methods consist of forecasts based on previous periods data with exponentially decaying influence when they become older;
- Exponential smoothing methods: These methods consist of a special case of exponential moving averages with notation ETS (error, trend, seasonality) where each component can be none (N), additive (A), additive damped (Ad), multiplicative (M) or multiplicative damped (Md). In a time series a trend represents the long-term direction or movement in the data. An additive or multiplicative trend (A,M) means that the trend is scaled by an additive or multiplicative factor, allowing it to increase or decrease proportionally over time. An additive or multiplicative damped trend (Ad,Md) indicates that the strength or impact of the trend diminishes as time progresses, leading to a more stable long-term behavior.

3.1 Optimal Parameters Estimation

Optimal parameters estimation consists of estimating or fine-tuning the exponential smoothing method coefficients which minimize the objective function sum of squared residuals (i.e., SSE) or forecast errors within the training data set:

$$Solver\ Objective = min\left(\sum_{t=1}^{n} e_t^2\right),$$

where n is the number of observations in the training range, and $e_t = y_t - \hat{y}_t$ are the forecast errors or residuals [25]. The coefficients to be computed are: α is the level smoothing coefficient, β is the trend smoothing coefficient, γ is the seasonal smoothing coefficient, and φ is the damping smoothing coefficient for the trend. The coefficients need to satisfy the following constraints:

$$0 \leq \alpha, \beta, \gamma \leq 1$$
$$0 < \varphi < 1$$

In this Section the forecasting models' parameters optimization is achieved by means of the Excel GRG nonlinear solver, which is an optimization engine based on the Generalized Reduced Gradient (GRG) algorithm, primarily used for solving nonlinear optimization problems. The characteristics of the Excel GRG solver are the following:

- Nonlinear Optimization: The GRG solver is designed to handle nonlinear optimization problems. These problems involve finding the optimal values of decision variables while considering a nonlinear objective function and possibly nonlinear constraints;
- Gradient-Based Method: The GRG algorithm is a gradient-based optimization method. It uses the derivatives (gradients) of the objective function and constraint functions with respect to the decision variables to guide the search for the optimal solution;
- Local Optima: Like many gradient-based methods, the GRG solver can converge to local optima, which are solutions that are optimal within a certain neighborhood but not necessarily the best possible solution globally;
- Initialization: The solver requires an initial guess for the decision variables. The choice of initial values can affect the convergence and the final solution.

The GRG nonlinear solver has a few advantages, including:

- It is relatively fast and efficient for solving small to medium-sized problems;
- It can handle a wide variety of nonlinear functions, including both convex and non-convex functions;
- It can handle problems with inequality constraints.

However, the GRG nonlinear solver also has some disadvantages, including:

- It can be sensitive to the initial solution. If the initial solution is not close to the optimal solution, the solver may not converge to a good solution;
- It may not be able to find the global minimum of the objective function;
- It can be difficult to use for complex problems with many decision variables.

Overall, the GRG nonlinear solver is an effective tool for solving nonlinear optimization problems in Excel. It is a good choice for problems that are relatively small to medium-sized and that do not have a lot of constraints. However, it is important to be aware of the solver's limitations, such as its sensitivity to the initial solution and its potential difficulty to find the global minimum. In this work we have used the GRG nonlinear solver to solve all the optimization problems.

3.2 Limitations of Exponential Smoothing Methods

Exponential smoothing methods have limitations and drawbacks. It is important to be aware of these limitations to make informed decisions about when and how to use them. Some of the limitations include:

- Limited Handling of Complex Patterns: Exponential smoothing methods are designed to capture simple patterns in data, such as trends and seasonality. However, they may struggle to model more complex patterns, such as sudden changes and irregular fluctuations;
- Lack of Mechanistic Understanding: Exponential smoothing methods are essentially statistical models that make predictions based on historical data patterns. They do not provide a mechanistic understanding of the underlying processes driving the data, which can be a limitation when trying to explain why certain forecasts are being generated;
- Sensitivity to Initialization: The forecasts produced by

exponential smoothing methods can be sensitive to the initial values and parameters chosen for the model. Small changes in initial conditions can lead to different forecasts, which might impact the stability and reliability of the results;
- Shortcomings for Long-Term Forecasting: Exponential smoothing methods are generally better suited for short- to medium-term forecasting. When attempting to make long-term predictions, these methods might not accurately capture underlying trends or structural changes in the data;
- Suboptimal Results with Noisy Data: Exponential smoothing methods assume that the data is relatively smooth and free from excessive noise or outliers. If the data contains a significant amount of noise, these methods might produce unreliable forecasts;
- Inability to Incorporate External Factors: Exponential smoothing methods focus solely on the historical data of the time series and do not directly incorporate external factors or additional information that might influence the forecasts;
- Model Complexity Limitation: While there are different variants of exponential smoothing methods that handle various levels of complexity, they might not be suitable for complex time series that require more sophisticated models such as ARIMA;
- Limited Diagnostic Tools: Exponential smoothing methods lack diagnostic tools to assess the goodness of fit and model accuracy. This can make it challenging to detect issues with the model or to identify cases where the model is performing poorly;
- Inadequate Handling of Seasonal Changes: If the seasonality in the data changes over time, exponential smoothing methods might struggle to effectively adapt to these changes;
- Model Assumptions: Like any modeling approach, exponential smoothing methods are based on certain assumptions about the data, such as stationarity and independence. Violations of these assumptions can lead to suboptimal forecasts.

Despite these limitations, exponential smoothing methods remain valuable tools in the forecasting toolkit. However, it is important to consider the characteristics of the data, the forecasting horizon, and the complexity of the patterns before deciding whether to use these methods or consider other alternatives that might better suit specific requirements.

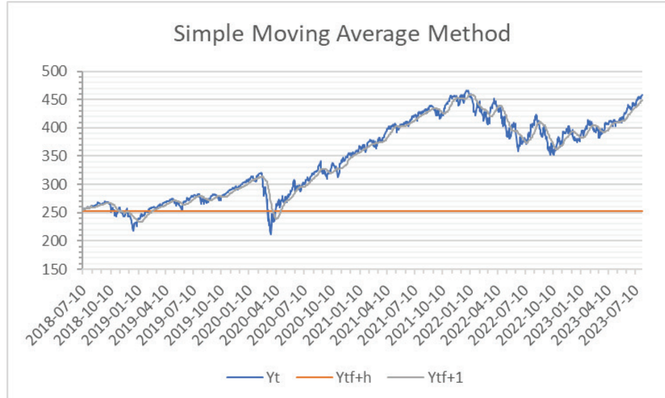
3.3 Simple Moving Average Method

The Simple Moving Average method consists of forecasts equal to the arithmetic mean of previous periods data. Supposing we consider *k* periods, then the simple moving average formula is:

$$\hat{y}_t = sma(k) = \frac{1}{k}\sum_{i=1}^{k} y_{t-i}.$$

The results are shown in Figure 3. The multistep forecasting $\hat{y}_{t+h}$ is done at the beginning of the testing range for the entire testing range and is the simple moving average of the last 21 periods in the training range projected all the way through the testing range. $\hat{y}_{t+1}$ represents the one-step forecasting without re-estimation, while y_t is the actual data from the testing range. The simple moving average smoothing is equally weighted.

Figure 3. Simple moving average in the testing range



3.4 Brown Simple Exponential Smoothing Method

The Brown Simple Exponential Smoothing method consists of forecasting a time series with no trend or seasonal patterns [17]. In ETS notation is expressed as ETS(A,N,N): error=additive, trend=none, seasonality=none, and is described by the following formulas:

$$\hat{y}_t = l_{t-1}$$
$$l_{t-1} = \alpha * y_{t-1} + (1-\alpha) * l_{t-2}$$
$$0 \le \alpha \le 1$$
$$initial\ l_{t-1} \approx initial\ y_{t-1}$$

where l_{t-1} is the previous period level forecast and α is the smoothing coefficient. Brown's Simple Exponential Smoothing, also known as the Simple Exponential Smoothing (SES) method, is a forecasting technique used to make short-term predictions for time series. It is a basic method that assumes the underlying pattern in the data is smooth and does not exhibit strong trends or seasonality. The method is particularly useful when the data lacks significant fluctuations or patterns. SES can be summarized as follows:

- *Basic Idea:* The method operates on the assumption that the future value of a time series can be predicted by assigning different weights to its past observations. Older observations are given lower weights, and more recent observations are given higher weights, as recent data is more relevant for predicting the near future;
- *Single Smoothing Parameter (Alpha):* The key parameter in SES is the smoothing parameter, which determines the weight assigned to the most recent observation when making the forecast;
- *Initial Forecast:* To start the forecasting process, an initial forecast is needed. This initial forecast can be based on the first observation in the time series or an average of the initial observations;

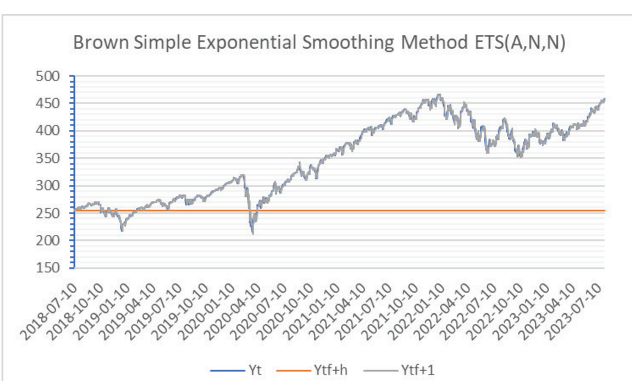
- *Updating the Forecast:* As new observations become available, the forecast is updated using the same formula, incorporating the new observation and the previous forecast;
- *Adaptability:* The SES method is adaptive in the sense that it automatically adjusts to changes in the underlying pattern of the time series. If the data starts showing new trends or patterns, the method will gradually adjust its forecasts to incorporate these changes;
- *Forecast Horizon:* The SES method is best suited for short-term forecasts. As the forecast horizon extends further into the future, the impact of older observations decreases significantly, and the method may not perform as well;
- *Smoothing Level:* The value of α controls the level of smoothing. When α is close to 0 then less weight is given to the most recent observation, and more weight is given to past observations. As a result, the forecast becomes smoother and more stable, and it reacts less to short-term fluctuations or noise in the data. Smaller α values are suitable when we want a more damped or conservative forecast, which is useful for data with minimal noise or when we want to emphasize the long-term trend. In contrast, when α is close to 1, more weight is placed on the most recent observations. As a result, the forecast is more responsive to recent changes in the data, making it less smooth and potentially more volatile. Larger α values are suitable when we want to react quickly to short-term changes in the data, which can be useful in situations where recent data points are highly informative.

The optimization of the α smoothing coefficient is performed by solving the following optimization problem in the training range:

$$\min\left(\sum_{t=1}^{n} e_t^2\right)$$
$$\textit{subject to}: 0 \leq \alpha \leq 1$$

The results are shown in Figure 4. Multistep forecasting is made at the beginning of the testing range for all the testing range. For one-step forecasting without re-estimation, we use the α smoothing coefficient computed with the GRC nonlinear solver in the training range, and we update the forecast with each new observation but without re-estimating the α smoothing coefficient.

Figure 4. Brown SES in the testing range



3.5 Holt Linear Trend Method

The Holt Linear Trend method consists of forecast with a linear trend pattern [18][19]. In ETS notation is expressed as ETS(A,A,N): error=additive, trend=additive, seasonality=none. The Holt Linear Trend Method, also known as Holt's Exponential Smoothing with Trend, is a forecasting technique that extends the SES method by incorporating a linear trend component. This makes it suitable for time series that exhibit both a trend and possibly some level of seasonality. The Holt Linear Trend Method works as follows:

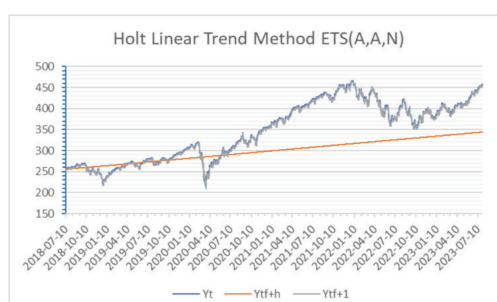
- *Components:* The method involves modeling two main components of a time series: the level (or base) and the trend;
- *Level Component:* The level component represents the average value of the time series data over time, excluding the trend and any seasonality. It is estimated using the exponential smoothing technique;
- *Trend Component:* The trend component accounts for the overall direction and pattern of change in the time series. It represents the rate at which the series is increasing or decreasing over time. The trend is estimated using a weighted average of the recent changes in the data;
- *Smoothing Parameters:* Holt's Linear Trend Method involves two smoothing parameters: alpha (α) for the level component and beta (β) for the trend component;
- *Initial Level and Trend:* Like other exponential smoothing methods, the initial level and trend values need to be set before starting the forecasting process. These initial values can be based on historical data or other domain-specific information.

The current period forecast is given by:

$$\hat{y}_t = l_{t-1} + h * b_{t-1}$$
$$l_{t-1} = \alpha * y_{t-1} + (1-\alpha) * (l_{t-2} + b_{t-2})$$
$$\textit{initial } l_{t-1} \approx \textit{initial } y_{t-1}$$
$$b_{t-1} = \beta * (l_{t-1} - l_{t-2}) + (1-\beta) * b_{t-2}$$
$$0 \leq \alpha, \beta \leq 1$$
$$\textit{initial } b_{t-1} \approx \textit{initial } y_t - y_{t-1}$$

where h is the number of forecasting steps, l_{t-1} is the previous period level forecast and b_{t-1} is the previous period trend forecast. The results are shown in Figure 5. In the training range the GRG nonlinear solver yields α = 0.9384, which is close to 1, and this means that more weight is given to the most recent observations vs older observations.

Figure 5. Holt linear trend in the testing range



3.6 Exponential Trend Method

The Exponential Trend method consists of forecast with an exponential trend pattern. In ETS notation is expressed as ETS(A,M,N): error=additive, trend=multiplicative, seasonality=none. The characteristics of the exponential trend method are:

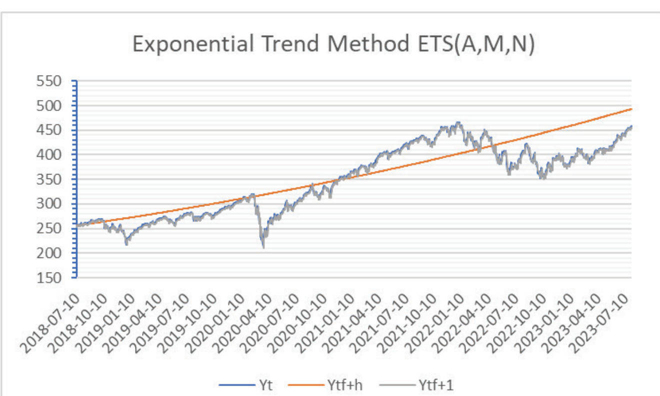
- *Error Component:* The "A" refers to the error term, indicating that the model assumes additive errors. This means that the difference between the actual value and the predicted value (after accounting for trend and seasonality) is treated as additive in nature;
- *Trend Component:* The "M" stands for multiplicative trend. This means that the trend component of the model is allowed to grow or decline at an exponential rate, which is a common characteristic of many time series patterns;
- *Seasonality Component:* The "N" stands for no seasonality. This means that the model does not account for any repeating patterns or seasonality in the time series.

The Exponential Trend method equations are:

$$\hat{y}_t = l_{t-1} * b_{t-1}^h$$
$$l_{t-1} = \alpha * y_{t-1} + (1-\alpha) * (l_{t-2} * b_{t-2})$$
$$0 \leq \alpha, \beta \leq 1$$
$$initial\ l_{t-1} \approx initial\ y_{t-1}$$
$$b_{t-1} = \beta * \left(\frac{l_{t-1}}{l_{t-2}}\right) + (1-\beta) * b_{t-2}$$
$$initial\ b_{t-1} \approx initial\ {}^{y_t}/_{y_{t-1}}$$

The results are shown in Figure 6. By comparing the $\hat{y}_{t+h}$ plots vs the actual data y_t it is possible to assess the difference between the additive trend component of the Holt's method depicted in Figure 5 and the multiplicative trend reported in Figure 6.

Figure 6. Exponential trend in the testing range



3.7 Garner Additive Damped Trend Method

The Gardner Additive Damped Trend method consists of forecast with damped linear trend pattern [20]. In ETS notation is expressed as ETS(A,Ad,N): error=additive, trend=additive damped, seasonality=none. The characteristics of Garner's method are:

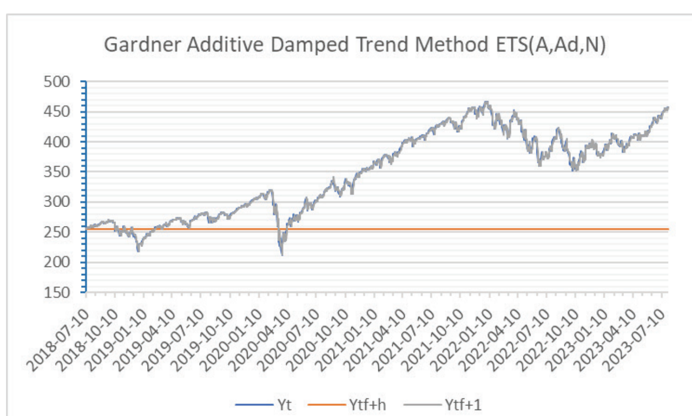
- *Error Component (A):* The "A" indicates that the model assumes additive errors. This means that the difference between the actual value and the predicted value (after accounting for trend) is treated as an additive term;
- *Damped Trend Component (Ad):* The "Ad" refers to the additive damped trend. This component models the trend in a way that dampens its influence over time. A damped trend implies that the trend's impact on the forecast diminishes as time progresses, reflecting the notion that extreme trends are unlikely to continue indefinitely;
- *Seasonality Component (N):* The "N" indicates that the model assumes no seasonality.

This forecasting method is particularly useful for time series data that exhibit an additive trend that is expected to dampen over time, and where seasonality is not present or is negligible. The Garner Additive Damped Trend method can be expressed by the formulas:

$$\hat{y}_t = l_{t-1} + \sum_{i=1}^{h} \varphi^i * b_{t-1}$$
$$0 < \varphi < 1$$
$$l_{t-1} = \alpha * y_{t-1} + (1-\alpha) * (l_{t-2} + \varphi * b_{t-2})$$
$$0 \leq \alpha, \beta \leq 1$$
$$initial\ l_{t-1} \approx initial\ y_{t-1}$$
$$b_{t-1} = \beta * (l_{t-1} - l_{t-2}) + (1-\beta) * \varphi * b_{t-2}$$

where φ is the damping smoothing coefficient. The results in the testing range are shown in Figure 7, where it is possible to observe the damping of the linear trend with respect to the Holt Linear Trend method depicted in Figure 5.

Figure 7. Gardner additive damped trend in the testing range



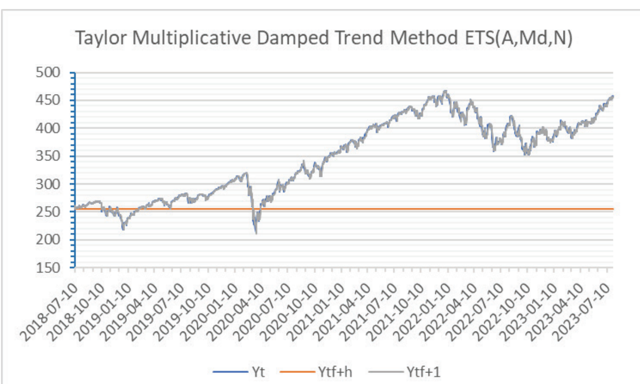
3.8 Taylor Multiplicative Damped Trend Method

The Taylor Multiplicative Damped Trend method consists of forecast with damped or restrained exponential trend pattern [21]. In ETS notation is expressed as ETS(A,Md,N): error=additive, trend=multiplicative damped, seasonality=none. The Taylor's method is particularly useful when dealing with time series that exhibit a damped or declining trend. The key feature of the Taylor's method is the damping parameter (φ), which dampens the trend over time, making it particularly suitable for situations where the trend is expected to decrease or become less influential as the forecast progresses further into the future. The Taylor Multiplicative Damped Trend method formulas are expressed as follows:

$$\hat{y}_t = l_{t-1} * b_{t-1}^{\sum_{i=1}^{h} \varphi^i}$$
$$0 < \varphi < 1$$
$$l_{t-1} = \alpha * y_{t-1} + (1-\alpha) * l_{t-2} * b_{t-2}^{\varphi}$$
$$0 \le \alpha, \beta \le 1$$
$$initial\ l_{t-1} \approx initial\ y_{t-1}$$
$$b_{t-1} = \beta * \frac{l_{t-1}}{l_{t-2}} + (1-\beta) * b_{t-2}^{\varphi}$$
$$initial\ b_{t-1} \approx initial\ \frac{y_t}{y_{t-1}}$$

The results are shown in Figure 8, where it is possible to observe the damping of Taylor Multiplicative Damped Trend method similar to Gardner's (Figure 7) or Holt-Winter's (Figure 12) damped methods.

Figure 8. Taylor multiplicative damped trend in the testing range



3.9 Holt-Winters Additive Method

The Holt-Winters Additive method consists of forecast with linear trend and additive seasonal patterns [22]. In ETS notation is expressed as ETS(A,A,A): error=additive, trend=additive, seasonality=additive. The characteristics of the Holt-Winters's method are:

- *Error:* This refers to the error component, where "A" implies that the errors are additive. This means that the deviations from the predicted values to the actual values are consistent and do not change based on the level of the time series;
- *Trend:* This refers to the trend component, where "A" indicates that the trend is additive. This implies that the trend is linear and increases or decreases by a constant amount over time;
- *Seasonality:* This refers to the seasonality component, where "A" implies that the seasonality is additive. In additive seasonality, the seasonal fluctuations have a consistent absolute effect on the time series.

An additive model is commonly used when seasonal variation is constant through time, while multiplicative model is commonly used when seasonal variation increases through time. The Holt-Winters Additive method is a time series forecasting technique that extends the Holt Linear Trend method by incorporating both seasonality and trend components. This method is particularly useful when dealing with time series that exhibit a linear trend and a constant amplitude of seasonality. It is designed to provide short- to medium-term forecasts for data with a regular seasonal pattern, and it is expressed by the following equations:

$$\hat{y}_t = l_{t-1} + h * b_{t-1} + s_{t-1}$$
$$l_{t-1} = \alpha * (y_{t-1} - s_{t-2}) + (1-\alpha) * (l_{t-2} + b_{t-2})$$
$$0 \le \alpha, \beta, \gamma \le 1$$
$$initial\ l_{t-1} \approx \frac{1}{m} \sum_{i=0}^{m-1} y_{t-1+i}$$
$$b_{t-1} = \beta * (l_{t-1} - l_{t-2}) + (1-\beta) * b_{t-2}$$
$$initial\ b_{t-1} \approx \frac{1}{m} \sum_{i=0}^{m-1} \frac{y_{t-1+i+m} - y_{t-1+i}}{m}$$
$$s_{t-1} = \gamma * (y_{t-1} - l_{t-2} - b_{t-2}) + (1-\gamma) * s_{t-1-m}$$
$$initial\ s_{t-1+i|i=0\to m-1} \approx y_{t-1+i|i=0\to m-1} - initial\ l_{t-1}$$

where y_{t-1} represents the observed previous period value, l_{t-1} represents the previous period level (or smoothed value), b_{t-1} represents the previous period trend (or slope), and s_{t-1} represents the previous period seasonal index. The α coefficient controls the weight assigned to the seasonally adjusted time series and the non-seasonal component of the time series; when α is close to 1, more weight is assigned to the seasonally adjusted component of the time series. The β coefficient controls the smoothing of the trend component: when β is close to 1, more weight is assigned to the changing level than to the past trend of the time series. The γ coefficient is the seasonality smoothing parameter: when γ is close to 1, more weight is assigned to the current seasonal component and less weight to the past seasonal component. The results are shown in Figure 9 and in Figure 10 (zoom-in).

Figure 9. Holt-Winters additive in the testing range

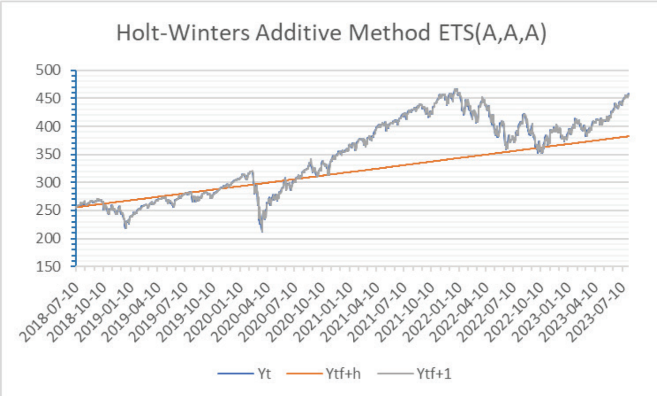
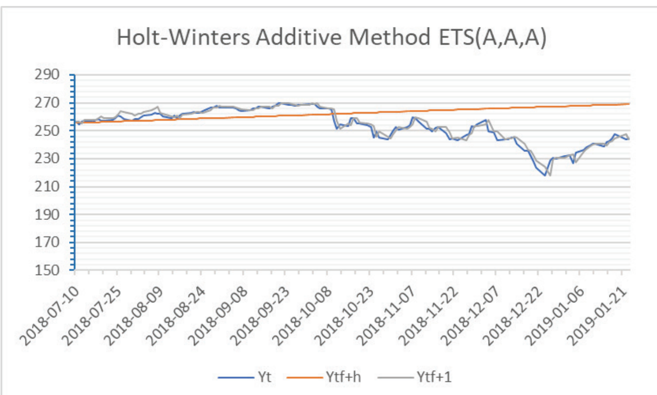


Figure 10. Holt-Winters additive in the testing range (Zoom-in)



3.10 Holt-Winters Multiplicative Method

The Holt-Winters Multiplicative method consists of forecast with linear trend and multiplicative seasonal patterns [22]. In ETS notation is expressed as ETS(A,A,M): error=additive, trend=additive, seasonality=multiplicative. The seasonality component is multiplicative, and this is the key difference with respect to the additive method described in Section 3.9. In multiplicative seasonality, the seasonal fluctuations have a proportional effect and exhibit a changing amplitude on the time series, rather than a consistent absolute effect as in additive seasonality. The Holt-Winters Multiplicative method is effective for generating short- to medium-term forecasts that capture both the trend and seasonality in the data, especially when the seasonality is not constant.

It is expressed by the following formulas:

$$\hat{y}_t = (l_{t-1} + h * b_{t-1}) * s_{t-1}$$

$$l_{t-1} = \alpha * \frac{y_{t-1}}{s_{t-2}} + (1-\alpha) * (l_{t-2} + b_{t-2})$$

$$0 \le \alpha, \beta, \gamma \le 1$$

$$initial\ l_{t-1} \approx \frac{1}{m} \sum_{i=0}^{m-1} y_{t-1+i}$$

$$b_{t-1} = \beta * (l_{t-1} - l_{t-2}) + (1-\beta) * b_{t-2}$$

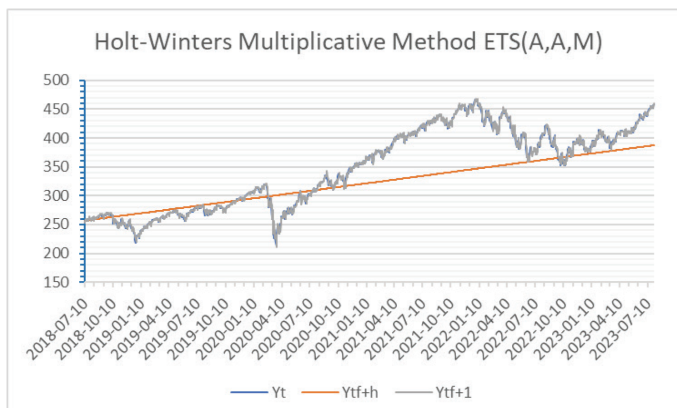
$$initial\ b_{t-1} \approx \frac{1}{m} \sum_{i=0}^{m-1} \frac{y_{t-1+i+m} - y_{t-1+i}}{m}$$

$$s_{t-1} = \gamma * \frac{y_{t-1}}{(l_{t-2} + b_{t-2})} + (1-\gamma) * s_{t-1-m}$$

$$initial\ s_{t-1+i|i=0 \to m-1} \approx \frac{y_{t-1+i|0 \to m-1}}{initial\ l_{t-1}}$$

The results are reported in Figure 11, where $\hat{y}_{t+h}$ is the multistep forecast done at the beginning of the testing range for the whole testing range which shows the additive type of trend and the multiplicative seasonality pattern.

Figure 11. Holt-Winters multiplicative in the testing range



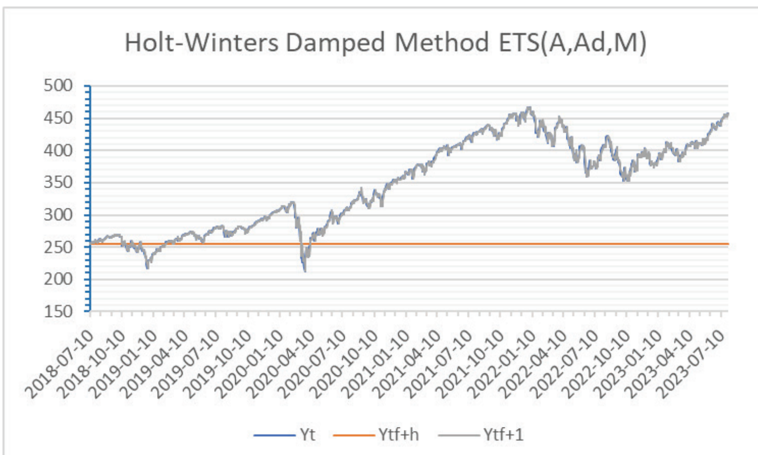
3.11 Holt-Winters Damped Method

The Holt-Winters Damped method consists of forecast with damped or restrained linear trend and multiplicative seasonal patterns [22]. In ETS notation is expressed as ETS(A,Ad,M): error=additive, trend=additive damped, seasonality=multiplicative, where "M" indicates that the seasonality component is multiplicative, and "Ad" indicates that the trend component is damped. If we believe that we may overforecast for the long horizon we can introduce a trend damping coefficient (φ). The Holt-Winters damped method is expressed by the following formulas:

$$\hat{y}_t = \left(l_{t-1} + \sum_{i=1}^{h} \varphi^i * b_{t-1}\right) * s_{t-1}$$
$$0 < \varphi < 1$$
$$l_{t-1} = \alpha * \frac{y_{t-1}}{s_{t-2}} + (1-\alpha) * (l_{t-2} + \varphi * b_{t-2})$$
$$0 \le \alpha, \beta, \gamma \le 1$$
$$initial\ l_{t-1} \approx \frac{1}{m} \sum_{i=0}^{m-1} y_{t-1+i}$$
$$b_{t-1} = \beta * (l_{t-1} - l_{t-2}) + (1-\beta) * \varphi * b_{t-2}$$
$$initial\ b_{t-1} \approx \frac{1}{m} \sum_{i=0}^{m-1} \frac{y_{t-1+i+m} - y_{t-1+i}}{m}$$
$$s_{t-1} = \gamma * \frac{y_{t-1}}{(l_{t-2} + \varphi * b_{t-2})} + (1-\gamma) * s_{t-1-m}$$
$$initial\ s_{t-1+i|i=0\to m-1} \approx \frac{y_{t-1+i|i=0\to m-1}}{initial\ l_{t-1}}$$

The results are shown in Figure 12, where $\hat{y}_{t+h}$ illustrated the additive damped trend together with the multiplicative seasonality.

Figure 12. Holt-Winters damped in the testing range



3.12 Method Selection and Forecasting Accuracy

Method selection consists of evaluating the goodness of fit and complexity trade-off within the training data set through the information loss criteria which penalize larger number of parameters, as discussed in the IFTA 2025 Journal [25]. The information loss criteria results for the exponential smoothing methods presented in this Section are reported in Table 1.

Table 1. Exponential smoothing information loss criteria results

	ETS(A,N,N)	ETS(A,A,N)	ETS(A,M,N)	ETS(A,Ad,N)	ETS(A,Md,N)	ETS(A,A,A,)	ETS(A,A,M)	ETS(A,Ad,M)
	Ytf	Ytf	Ytf	Ytf	Ytf	Ytf	Ytf	Ytf
sse	5564.70877	5556.36212	5557.97423	5564.70877	5564.69549	5572.53874	6101.29585	5574.67676
aic	1666.81490	1663.67530	1664.66858	1670.81490	1670.80673	1675.62935	1986.01647	1678.94278
aicc	1666.81841	1663.68232	1664.67560	1670.82660	1670.81843	1675.64104	1986.02817	1678.96033
bic	1679.09203	1682.09099	1683.08428	1695.36916	1695.36098	1700.18360	2010.57073	1709.63560

Regarding AIC the forecasting method with less information loss is the Holt Linear Trend method ETS(A,A,N), while for BIC the forecasting method with the smaller information loss is the Brown Simple Exponential Smoothing method ETS(A,N,N), which has a minor BIC value. When two different forecasting models, ETS(A,A,N) has the lowest AIC, while ETS(A,N,N) has the lowest BIC, we are faced with a common dilemma in model selection. Each criterion has its own approach to penalizing model complexity, and they can lead to different model selections:

- ETS(A,A,N) with lowest AIC: AIC tends to favor models that provide the best predictive performance while considering model complexity. Lower AIC suggests a better trade-off between goodness of fit and model complexity, making ETS(A,A,N) the preferred choice when prediction accuracy is a primary concern. Moreover, as discussed in [25] AIC is the preferred choice with larger sample size and allows for residuals heteroscedasticity, which are two conditions typical of financial data;
- ETS(A,N,N) with lowest BIC: BIC is more conservative in penalizing model complexity and typically favors simpler models. Lower BIC suggests that ETS(A,N,N) provides the simplest adequate explanation of the data, which minimizes the risk of overfitting and focuses on model parsimony.

Based on these considerations, we selected model ETS(A,A,N), which shows the best forecasting accuracy in the testing range for one-step forecasting without re-estimation (Table 3).

The forecasting accuracy is assessed by means of the metrics presented in [25], and is performed on both the multistep forecasting and the one-step forecasting without re-estimation in the testing range. It is worth noting that MASE is computed considering the absolute values of the forecast errors or residuals divided by the seasonal random walk mean absolute error. We use the seasonal random walk because we assume a monthly seasonality approximated as 21 days. For evaluating the forecasting accuracy, we consider two metrics: RMSE and MAPE. For multistep forecasting, the forecasting method with the lowest RMSE and MAPE (i.e., the highest forecasting accuracy) is the Exponential Trend Method ETS(A,M,N), as reported in Table 2.

Table 2. Exponential smoothing multistep forecasting accuracy results

	SMA	ETS(A,N,N)	ETS(A,A,N)	ETS(A,M,N)	ETS(A,Ad,N)	ETS(A,Md,N)	ETS(A,A,A,)	ETS(A,A,M)	ETS(A,Ad,M)
	Ytf+h	Ytf+h	Ytf+h	Ytf+h	Ytf+h	Ytf+h	Ytf+h	Ytf+h	Ytf+h
mae	96.03723	93.44190	52.57341	32.39034	93.44190	93.44176	37.17376	35.31511	93.33400
rmse	117.25807	114.83651	67.63004	39.65932	114.83651	114.83637	49.85908	47.61395	114.73433
mape	24.75935	24.02651	13.50254	9.19847	24.02651	24.02647	9.75671	9.34106	23.99629
mase	25.15296	24.47322	13.76942	8.48330	24.47322	24.47319	9.73612	9.24933	24.44496

For one-step forecasting without re-estimation the Brown Simple Exponential Smoothing method ETS(A,N,N) yields both the lowest RMSE and MAPE values, hence the highest forecasting accuracy, as summarized in Table 3.

Table 3. Exponential smoothing one-step forecasting without re-estimation accuracy results

	SMA	ETS(A,N,N)	ETS(A,A,N)	ETS(A,M,N)	ETS(A,Ad,N)	ETS(A,Md,N)	ETS(A,A,A,)	ETS(A,A,M)	ETS(A,Ad,M)
	Ytf+1	Ytf+1	Ytf+1	Ytf+1	Ytf+1	Ytf+1	Ytf+1	Ytf+1	Ytf+1
mae	8.39953	3.00264	3.71632	3.56371	3.00264	3.00643	3.02664	3.26286	3.01325
rmse	11.12178	4.32304	4.83200	4.68207	4.32304	4.32714	4.35780	4.56675	4.34197
mape	2.49315	0.88561	1.10553	1.06146	0.88561	0.88710	0.89639	0.96756	0.88967
mase	2.19991	0.78642	0.97333	0.93337	0.78642	0.78741	0.79270	0.85457	0.78919

4. Conclusions

This paper has presented an in-depth analysis of exponential smoothing methods for financial time series forecasting, highlighting their effectiveness, practicality, and role relative to other forecasting approaches, like the Simple Moving Average. The analysis confirms that exponential smoothing techniques can achieve robust predictive performance in financial applications, despite their simplicity. In our study, the various forms of exponential smoothing — including simple (single) smoothing for level predictions, Holt's double smoothing for trends, and the Holt-Winters approach for seasonality — consistently generated accurate forecasts. The damped trend exponential smoothing method demonstrated consistent results, aligning with previous findings that it is difficult to outperform as a general-purpose forecasting tool. These outcomes reinforce the status of exponential smoothing as a competitive forecasting approach in finance, due to its empirical reliability.

A comparative perspective indicates that while advanced forecasting techniques (such as ARIMA, state-space models, and machine learning algorithms) may offer certain advantages, exponential smoothing methods remain remarkably resilient. When data exhibit evolving trends or require rapid updating with new observations, the adaptive nature of exponential smoothing — continually recalibrating forecasts with each new data point — proved beneficial. Meanwhile, machine learning and deep learning models have shown promise in capturing complex nonlinear patterns in financial data, yet these models come with higher complexity and computation cost, and often demand large training datasets, making them less interpretable and sometimes prone to overfitting in small-sample or non-stationary financial environments. In contrast, exponential smoothing provides a modeling approach that distills the data's salient features (level, trend, seasonality) into a few intuitive parameters. The performance of exponential smoothing observed in this research suggests that, even if "black-box" AI models proliferate, there is enduring value in these classical statistical techniques — both as standalone forecasting tools and as components of hybrid modeling strategies. Indeed, our results resonate with the view that exponential smoothing methods could serve as a first-line benchmark in forecasting practice, against which more elaborate models are measured for incremental improvement.

Beyond raw forecast accuracy, several broader implications emerge from this work. Exponential smoothing's simplicity and transparency make it particularly appealing for practical deployment in financial forecasting and technical and quantitative analysis. Analysts can easily explain the logic of the forecasts (e.g., the emphasis on recent data and the treatment of trends), which is important for decision-makers who require understanding of the model's behavior. The low computational requirements enable rapid re-estimation and updating, a valuable trait in fast-moving financial markets where new data arrive continuously. Moreover, because exponential smoothing models are relatively parsimonious, they are less susceptible to instabilities when regimes shift — a common occurrence in finance — compared to heavily parameterized models. That said, it is also clear that no single method dominates in all situations. While exponential smoothing consistently performed strongly overall, there are cases in which incorporating additional information or more complex dynamics could further improve forecasts (for example, integrating volatility clustering through GARCH-type models, or using multivariate approaches to exploit cross-series correlations). This suggests a fruitful direction for future research: hybrid approaches that combine the strengths of exponential smoothing with other techniques.

In conclusion, our study reaffirms that exponential smoothing methods are not only historically important but also highly effective for modern financial time series forecasting. They offer a blend of accuracy, simplicity, and adaptability that is well-suited to the needs of both researchers and practitioners in technical and quantitative analysis. Even as the field of forecasting advances with new algorithms, exponential smoothing provides a strong foundation and a point of reference for evaluating the improvements. We advocate that financial analysts, traders, and investors continue to consider exponential smoothing as a go-to approach, especially in cases where data exhibit clear structural patterns or when model interpretability is paramount. Ultimately, the long-standing success of exponential smoothing in this and numerous other studies serves as a reminder that in financial forecasting, as in many domains, sophisticated solutions should be measured against robust simple methods that have stood the test of time.

5. Next Steps

Looking ahead, the forthcoming issues of the IFTA Journal will extend this research by providing an in-depth examination of additional forecasting methodologies, notably the ARIMA, GARCH, and hybrid ARIMA-GARCH models. These techniques are well-established in financial time series analysis: ARIMA (AutoRegressive Integrated Moving Average) models have been widely used to capture linear trends and dependencies in non-stationary price data, while GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) models focus on modeling time-varying volatility and volatility clustering in asset returns. By integrating the two, hybrid ARIMA-GARCH approaches leverage the strength of each method, jointly modeling the expected value and conditional variance of a series to provide a more comprehensive forecasting framework. Initial empirical findings underscore the promise of such hybrid models, showing that they can adapt to dynamic market conditions and achieve superior fit to volatile financial time series. This makes them a compelling subject for further detailed analysis in upcoming IFTA Journal issues.

Future editions of the IFTA Journal will therefore feature rigorous comparative analyses of the ARIMA, GARCH, and ARIMA-GARCH techniques across diverse market scenarios and considering non-Gaussian distributions. Each model's forecasting performance and robustness will be scrutinized using standard metrics of predictive accuracy and risk evaluation, thereby highlighting the strengths and limitations of each approach under varying conditions. By examining use-cases ranging from stable trending markets to highly volatile regimes, the forthcoming research aims to delineate the domains in which each model excels or underperforms. Such a comprehensive evaluation, to be presented in detail in the next IFTA Journal issues, will enrich the toolkit of technical and quantitative analysts with deeper insights into these forecasting techniques and guide practitioners in selecting appropriate models for different financial forecasting tasks.

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The GSR Bands

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Abstract

This study offers an innovative vision that transcends the concept, uses, and importance traditionally given to opening gaps in terms of market compression, and their use in financial asset investment. By using the concept of Macrostructure of an asset, or decomposition of its price as a formula of equilibrium between the gap and market component, and its comparison with traditional variables such as volume, historical volatility and implied volatility, it is observed how the opening gaps are the supports or resistances of variables such as volume or volatility of an asset. This study demonstrates how the comparison through the technical analysis point of view of a volatility index of an asset, and its opening gaps taking into account the Fibonacci series or prime numbers or GSR Bands, allows to detect quite accurately the total lows of assets such as S&P500, DAX40 or Crude Oil, detecting with an accuracy of 0 or 1 day more than 50% of these total market lows.

Introduction

Opening gaps, understood as the difference in price that occurs between the closing price of a financial asset of any type at t–1 and t, and the opening price at t, are a topic rarely addressed in financial literature. In fact, when searching for academic papers on platforms such as SSRN or Google Scholar, only a handful of studies on this subject can be found. These studies can be categorized into three major areas:

- Those focusing on price behavior before and after the opening gap, with notable contributions from Caporale and Plastun (2017), Plastun et al. (2019), and Plastun et al. (2020).
- Those examining the relationships between gaps and market development (both before and after), highlighting research by Branch and Ma (2012), as well as Cliff, Cooper, and Gulen (2008).
- Those emphasizing the significance of opening gaps and attempting to predict them based on price movements in other markets, with key contributions from De Gooijer, Diks, and Gatarek (2009).

Given the definition of an opening gap and the limited number of authors who have explored this topic, it is essential to consider the factors contributing to its existence. The following causes have been identified by Caporale and Plastun (2017):

- Time differences between the closing and opening periods of the market, particularly before holidays and weekends
- The presence of an after-hours market.
- Unexpected news or corporate announcements, many of which occur at market close (e.g., terrorist attacks, corporate earnings reports, OPEC meetings).
- Significant shifts in the supply and demand of an asset, including changes in volume and liquidity.
- Opening and closing auctions.
- Existing mechanisms to manage extreme volatility, such as Circuit Breakers and Volatility Halts in the U.S. market.

In addition to these factors, Branch and Ma (2012) identified further contributors, the behavior of market makers, pending buy and sell orders, the presence of stocks that are difficult to value and costly to arbitrage.

Furthermore, considering the existence of two major markets the spot market and the derivatives (futures) market which often have nearly identical closing prices but significantly different trading hours, it is reasonable to assume a relationship between these markets. There must be an element that connects them. Consequently, another cause of opening gaps must be considered, the difference in trading hours between spot and futures markets. The evolution of the futures market from the closing of the spot market until its reopening determines the opening gap in the spot market, in addition to the carry of the futures contract, which consists of dividends minus the interest charged for financing the purchase (Cagigas, 2023).

Additionally, following the logic of the existing relationship between spot and futures markets, past market movements are expected to influence the opening gaps of subsequent markets. De Gooijer, Diks, and Gatarek (2009) demonstrated that the evolution of the Asian market affects the direction and magnitude of the gap in the European market, while the European market, in turn, influences the gap in the American market.

By understanding the factors that explain the existence of opening gaps, this study offers a new perspective on them, highlighting their relevance in understanding market behavior and informing trading strategies. Therefore, this study graphically compares the opening gap of an asset with fundamental variables such as market performance, volatility, and the concept of market seasonality.

Macrostructure of an asset

Traditionally, the daily profitability of an asset has been calculated as the difference in closing prices. However, if the total profitability of an asset is decomposed, accumulated, and plotted as the sum of its two basic components, the Gap and the Market, it forms what this study defines as the Macrostructure of an asset. This Macrostructure represents a new approach to visualizing market prices, providing additional information beyond traditional representation methods such as lines, bars, or candlesticks.

Based on the chart presented in the introduction, each component can be formulated in percentage terms as follows:

Gap component: The daily return is produced by the price difference between the market close at t-1 and the opening at t. It can be defined as the return generated after the regular trading hours of the main stock exchanges.

Ln (Open t / Close t-1)

Market component: The daily return generated by the normal course of open market trading occurs from the opening at t to the closing at t.

Ln (Close t / Open t)

Total market component: The return is generated between the closing price at t and the closing price at t-1-

Ln (Close t / Close t-1)

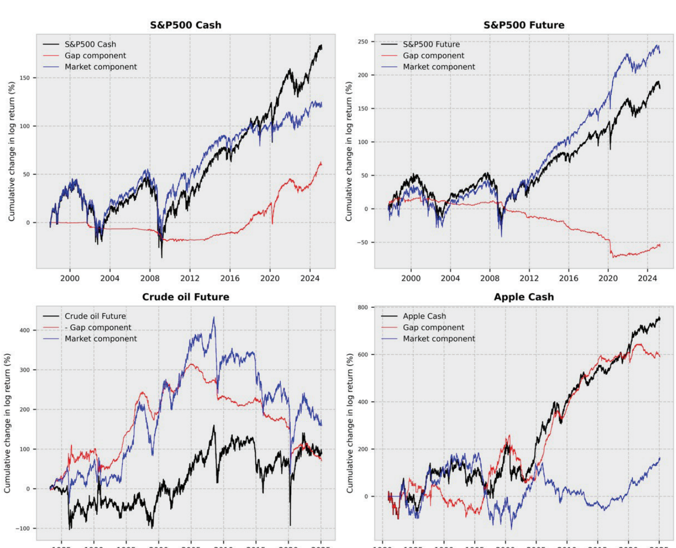
Logically, this division is only meaningful when the sum of the return from the gap component and the return from the market component equals the total return of the asset.

Total, Market = Gap + Market

Ln (Close t / Close t-1) = Ln (Open t / Close t-1) +Ln (Close t / Open t)

As an example, the Macrostructures of four well known assets are presented below: the S&P500 cash and futures, the Crude Oil future, and the Apple stock. It should be noted that each asset, beyond those analyzed in this study, has its own unique Macrostructure, distinct from other assets.

Figure 1: Macrostructure of S&P500 cash and future, Oil crude wti and Apple



In the 5 charts above we observe 3 important things:

First, the existence of an opposite behavior between the gap and market component, as clearly shown in the case of the Apple stock and in the S&P500 future, which fits with the negative correlation results found by B. Branch, A. Ma. (2012). As well as the fact that the gaps of the spot and future are opposite to each other, a fact that happens in many more assets than the S&P500, and which is explained by the stock of 2 markets with different trading hours.

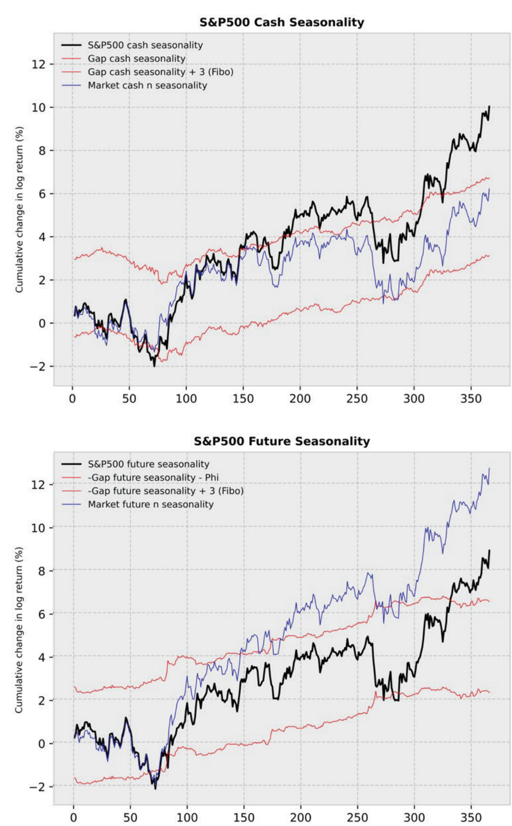
Secondly, the opening gap marks the market lows in assets such as the Crude Oil future, although it should be noted that this also happens in other assets such as the german DAX40.m

And thirdly, although it is not the subject of this study, we emphasize that this Macrostructure could explain why price movements occur after the appearance of the opening gaps, or movements to cover the gaps. Since it is logical to think that if the gap component is bullish in time and the market bearish, the bullish gaps (SELL position) will be covered in a better way than the bearish ones (BUY position), and vice versa.

Opening gaps and seasonality of assets

As we saw in the Macrostructure of the Crude Oil future, the opening gaps show a priori, the ability to detect market lows in a natural way. Knowing this, we wonder if these same gaps also have the ability to detect market lows, through the seasonal behavior of the asset. To answer this question, and having a sample of data since 2000 of the S&P500 spot and futures, we proceed to calculate and plot the seasonality of the gap, market and total market components of these two assets.

Figure 2: S&P500 seasonality since the year 2000



The previous graphs illustrate how, in both the S&P 500 spot and futures markets, the seasonal gap represents the minimum values of this asset over the last 24 years of data. In the case of the futures market, if the Phi number is subtracted from the seasonality of the gap, and if the number 3 is added to the seasonality of the opening gap, the result highlights the maximums of the seasonality of the S&P 500 spot and futures.

Given this intriguing observation, it is relevant to examine how the seasonality of the S&P 500 relates to the seasonal gap components of the VIX, the volatility index of the S&P 500, which measures the expected 30 day implied volatility of this stock index. To address this, a detailed analysis of the seasonality of the VIX spot and futures is conducted, starting from 2009 due to the limited availability of data on this asset. Subsequently, this seasonality is compared to that of the S&P 500 for the same period.

Figure 3: VIX seasonality 2009-2024

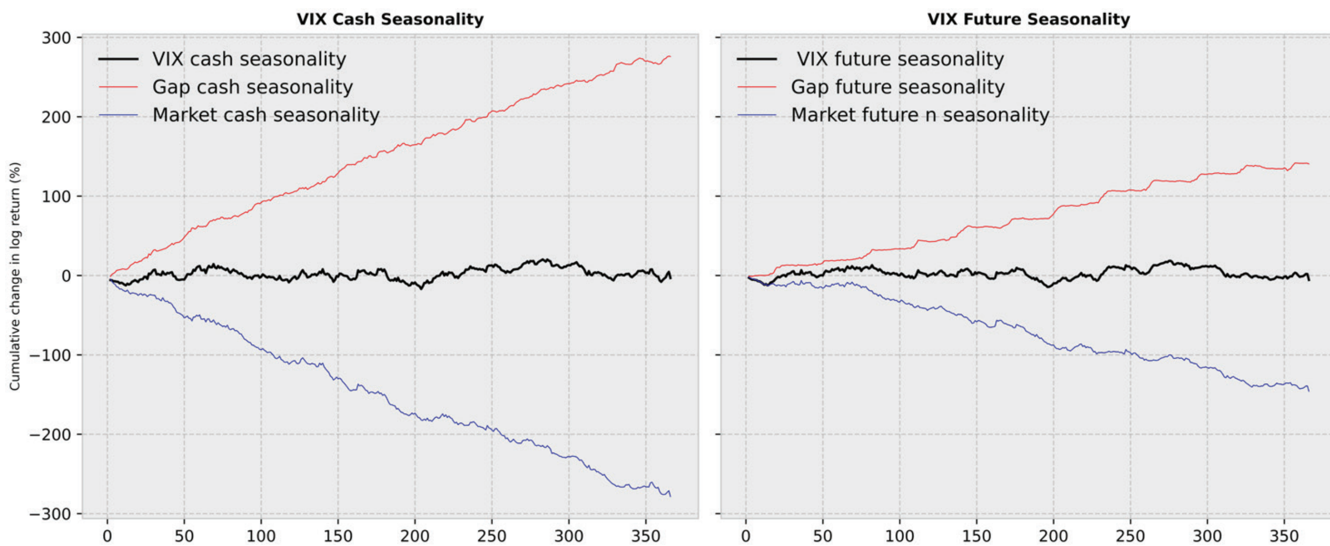


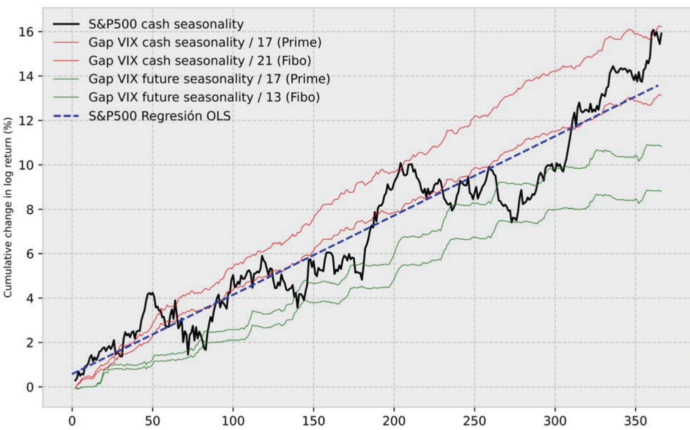
Table 1: Relationship between the slopes of the Gap and Market of the VIX

Degrees of inclinatiom							Phi	
Gap cash	37.16	Relationship	Gap	Market	Gap deviation	Market deviation	Value	Formula
Market cash	-36.34	Cash / Future	1.602	1.592	0.975%	1.65%	1.618	$\varphi_+ = \frac{\sqrt{5}+1}{2}$
Gap future	23.19	Future / Cash	0.624	0.628	-0.965%	-1.62%	0.618	$\varphi_- = \frac{\sqrt{5}-1}{2}$
Market future	-22.83	Sum	2.226	2.220	0.431%	0.72%	2.236	$\varphi_{sum} = \varphi_+ + \varphi_-$

The results indicate that the relationship between the seasonality of the gap and market components of the VIX spot and futures corresponds to the Phi number or a value very close to it. This is a remarkable finding, reinforcing the idea that the minimum of the seasonality of the S&P 500 futures is its seasonalized gap minus the Phi number, while its highs are represented by the gap plus 3. It is worth noting that Phi is the ratio found in the Fibonacci sequence, and 3 is a number belonging to this sequence.

Building on these results and recognizing the significance of the Phi number within them, the analysis now explores how the seasonality of the S&P 500 since 2009 can be further explained, or even better understood, through the gaps of the VIX index in both the spot and futures markets. A graphical representation demonstrates how dividing these values by the Fibonacci sequence and the prime number series allows for the accurate detection of most of the highs and lows in the seasonality of the S&P 500 cash.

Figure 4: VIX gap seasonality and S&P500 future seasonality regression line (2009-2024)



Opening gaps and volume, historical volatility

In addition to the four essential variables that comprise stock market data namely, the opening, high, low, and closing prices two other critical variables must be considered. Volume, which represents the number of contracts traded, serves as an inherent market variable that complements the previously mentioned four. Historical volatility, on the other hand, measures the speed at which prices fluctuate and is typically calculated using the deviations between closing prices or as applied in this study, through the deviations between the differences in maximum and minimum prices.

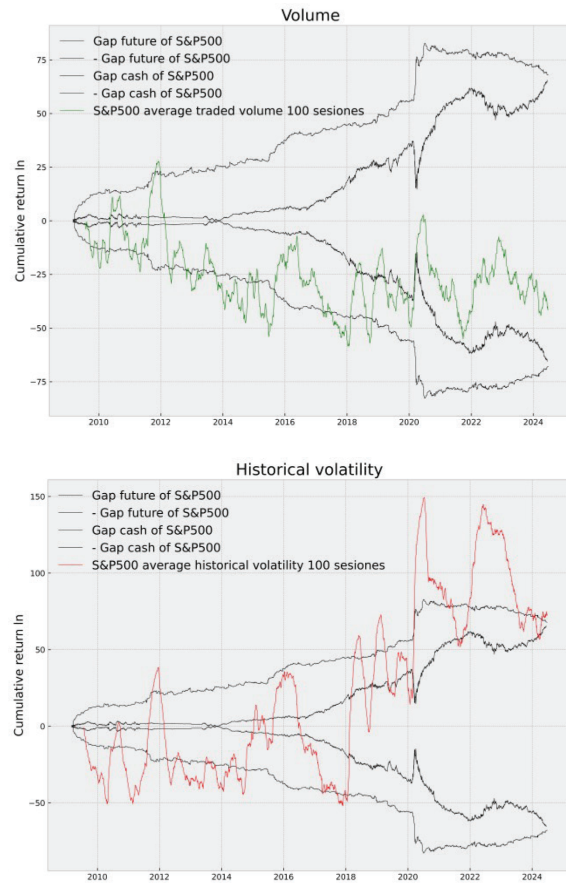
As is widely recognized, the relationship between volatility and volume with the price evolution of an asset can be either inverse or direct. This means that price movements can exhibit sharp increases or declines with rising volume (direct or inverse relationship). Additionally, volatility tends to increase in response to significant price swings. Although volatility and price movements are often inversely correlated given that price declines are usually rapid and steep, whereas price increases tend to be more gradual exceptions to this pattern can occur.

With these considerations in mind, and having previously demonstrated the significance of opening gaps in price behavior and seasonality, this study now examines the relationship between volume, historical volatility, and opening gaps. To explore this relationship, volume and volatility are first calculated using a 100 period moving average of both variables, which is then applied to the following formula:

Ln (Volume or Volatility in t / Volume or Volatility in t-1)

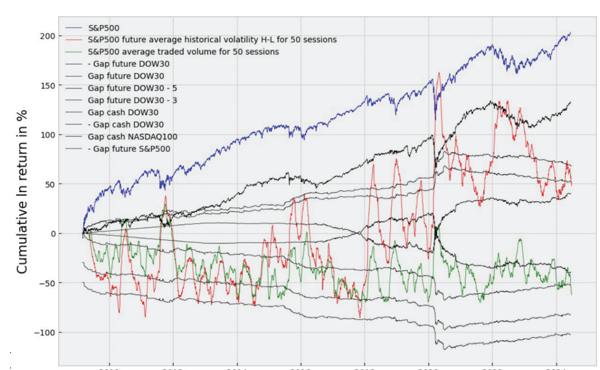
These variables are then accumulated and plotted alongside the positive and negative gaps of the S&P 500 spot and futures.

Figure 5: Relationship of volume and historical volatility to S&P500 gaps



It is curious to observe how volume or volatility do not fluctuate as freely as previously thought, but rather the opening gaps of the index itself, in this case the S&P500, act as a pivot point for these two variables. However, and despite this amazing fact, it can be seen that not all trend changes in volume or volatility are captured by the opening gaps of the S&P500 spot and futures. Bearing in mind that many of the stocks that make up the S&P500 are also included in the other two major American indices, namely the NASDAQ100 and the DOW30, the analysis proceeds by creating the same charts, but this time including the gaps of the three indexes, rather than just those of the S&P500.

Figure 6: GSR Bands: volume and historical volatility of S&P500

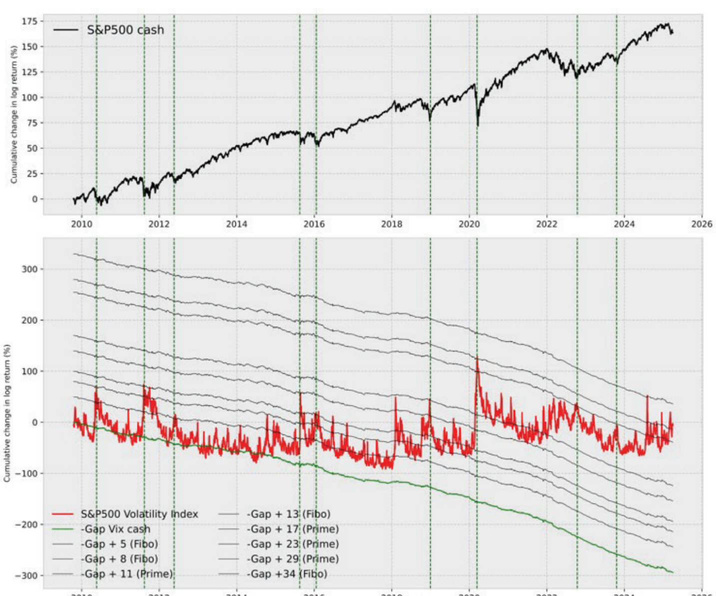


and DOW30, it can be observed how the trading volume of the S&P500 oscillates between the opening gaps of these indexes. However, it is the historical volatility of the S&P500 that presents the best result, with each turn in its movement aligning perfectly with these opening gaps, a phenomenon referred to as the GSR Bands. Taking this into account, the pertinent question arises: what use do the GSR Bands have in trading? Upon closer inspection of the chart above, it can be seen that in most cases, a market low occurs when volatility makes a high and hits an opening gap (red dashed line). Conversely, a market high occurs when volatility makes a low in an opening gap (dashed green line). As previously mentioned, the relationship between the evolution of the S&P price and its historical volatility is, in most cases, inverse.

GSR Bands: opening gaps and implied volatility

Having analyzed the volume and historical volatility of the S&P500, and observed how these two variables fluctuated between the opening gaps of its benchmark and similar indices, the next step is to consider what patterns might exist between the opening gaps of the S&P500 or VIX index and the opening gaps of its benchmark. The analysis now turns to investigating potential patterns between the implied volatility of the S&P500 or VIX index and the opening gaps. The VIX, or "fear index," has the advantage of being a direct daily volatility measure, which can be easily interpreted due to its "spike" shape. This is done without resorting to moving averages, as was the case with historical volatility, which would detect market highs or lows with a certain delay. The next step is to plot the VIX along with its opening gaps, taking into account the Fibonacci series, prime numbers, and the S&P500 index.

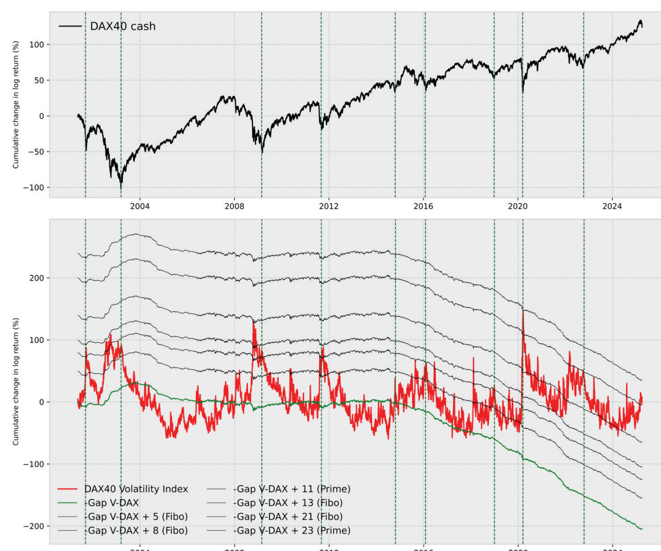
Figure 7: GSR Bands. Implied volatility index of S&P500



It is checked how the implied volatility of the S&P500, measured through the VIX index, fluctuates between the GSR Bands, now calculated as the sum of the VIX gap with the Fibonacci series and the prime number series. Again, many of the market lows reached by the S&P500 are observed when the VIX stops right at one of the gap lines of the GSR Bands.

It is worth noting that this phenomenon is not exclusive to the American index, as the same pattern is seen for any asset with its corresponding implied volatility index, such as the German DAX40 or the WTI crude oil future. Below is a backtest of the GSR model, along with the difference in days between the lows detected by the model and the actual date of the lows produced in the S&P500 from the market low. It is highlighted that the deviation in the number of days is consistently low on both the average and median.

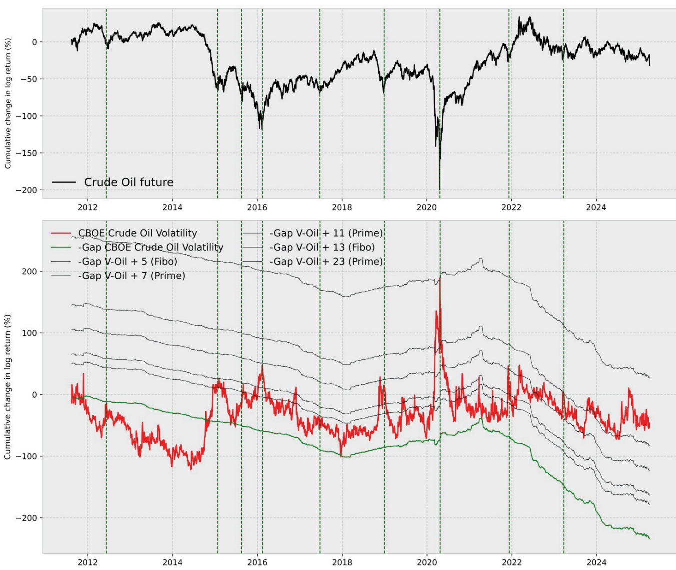
Figure 8: GSR Bands. Implied volatility Index of DAX40



It is highlighted that both for the case of the S&P500 and for the case of DAX40 and the subsequent Crude Oil, the crash of a volatility index with its opening gaps taking into account the Fibonacci series and prime numbers, is not only able to detect the large market lows, or total lows, but it is also able to detect other smaller lows or partial lows. The reason for not marking them with vertical lines on the chart is to facilitate the graphical understanding of the model to the reader, reducing the number of lines on the chart, and to generate a simpler and more interpretable chart.

Next, and to conclude the examples of the application of the GSR Bands, the model is calculated and plotted for the case of Crude Oil futures since 2011.

Figure 9: GSR Bands, implied volatility Index of Oil wti



This section concludes by highlighting the great capacity of GSR Bands to detect market lows, but this model has the disadvantage that a priori, we do not know in which gap band the implied volatility will stop and generate a market low in the analyzed asset. However, the model does provide us with possible price zones where the market will reverse its downward trend to upward, so it is very feasible to carry out a strategy with stop losses close to these price zones, where it is very likely that the price will turn around.

Effectiveness of GSR Bands

The GSR Bands graphs applied on the implied volatility indexes of the S&P500, DAX40 and Crude Oil, show that their large market lows occur graphically when their implied volatility indexes touch or collide with their opening gaps, taking into account the Fibonacci series and prime number series. This article finally asks what is the effectiveness or accuracy of the GSR Bands, that is, what is the deviation between reality and the model.

For this purpose, Table 2 shows the dates and prices of all the total minimums experienced by the S&P500 spot, DAX40 and Crude Oil futures, and the dates and prices at which these were detected by the GSR Bands, showing the deviations that occurred between the real minimums and the minimums detected by the model in this detailed study.

Table 2: Deviation in days and price (%) of GSR Bands with respect to real minimums

Asset	Asset Lows		Shock Implied Volatility - Gap		Deviation	
	Date	Price	Date	Price	Days	Price (%)
DAX40	2001-09-21	3787.23	2001-09-21	3787.23	0	0.00%
	2003-03-12	2202.96	2003-01-27	2643.80	-32	20.01%
	2009-03-06	3666.41	2008-10-16	4622.81	-101	26.09%
	2011-09-22	5164.21	2011-09-12	5072.33	-8	-1.78%
	2014-10-15	8571.95	2014-10-16	8582.90	1	0.13%
	2016-02-11	8752.87	2016-02-11	8752.87	0	0.00%
	2018-12-27	10381.51	2018-12-27	10381.51	0	0.00%
	2020-03-18	8441.71	2020-03-18	8441.71	0	0.00%
	2022-09-29	11975.55	2022-09-29	11975.55	0	0.00%
Crude Oil	2012-06-28	77.69	2012-06-01	83.23	-19	7.13%
	2015-03-17	43.46	2015-02-05	50.48	-28	16.15%
	2015-08-24	38.24	2015-09-01	45.41	6	18.75%
	2016-02-11	26.21	2016-02-11	26.21	0	0.00%
	2017-06-21	42.75	2017-07-11	45.23	14	5.80%
	2018-12-24	42.82	2018-11-23	50.59	-21	18.15%
	2020-04-21	11.57	2020-04-21	11.57	0	0.00%
	2021-12-01	65.37	2021-11-30	65.85	1	0.73%
	2023-03-17	66.93	2023-03-17	66.93	0	0.00%
S&P500	2010-07-02	1022.60	2010-05-20	1071.60	-31	4.79%
	2011-08-08	1119.50	2011-08-08	1119.50	0	0.00%
	2012-06-04	1278.20	2012-06-01	1278.00	-1	-0.02%
	2015-08-25	1867.60	2015-08-24	1893.20	-1	1.37%
	2016-02-11	1829.10	2016-01-20	1859.30	-16	1.65%
	2018-12-24	2351.10	2018-12-24	2351.11	0	0.00%
	2020-03-23	2237.40	2020-03-16	2386.11	-5	6.65%
	2022-10-12	3577.03	2022-09-26	3655.04	-12	2.18%
	2023-10-27	4117.37	2023-10-20	4224.16	-5	2.59%
Average	DAX40 cash				**-15.6**	**4.94%**
	Crude Oil future				**-5.2**	**7.41%**
	S&P500 cash				**-7.9**	**2.14%**
	TOTAL				**-9,6**	**4.83%**

Overall, the GSR Bands model detects market lows 9.6 days before they occur, which means detecting the low 4.83% above the actual market low. Although there are differences by assets, since, in the DAX40, these are detected 15.6 days before, and at a price 4.94% above their real minimums, in Crude Oil 5.2 days before at a price 2.24% above the minimum, and in the S&P500 7.9 days before, at a price 2.14% above the total market minimum.

Finally, the great capacity of the GSR Bands to detect market lows is highlighted, since 51.85% of all the lows were detected 0 or 1 day before they occurred, 14.81% between 2 and 10 days before, and only 33.33% were detected more than 10 days before.

GSR-MINI Bands

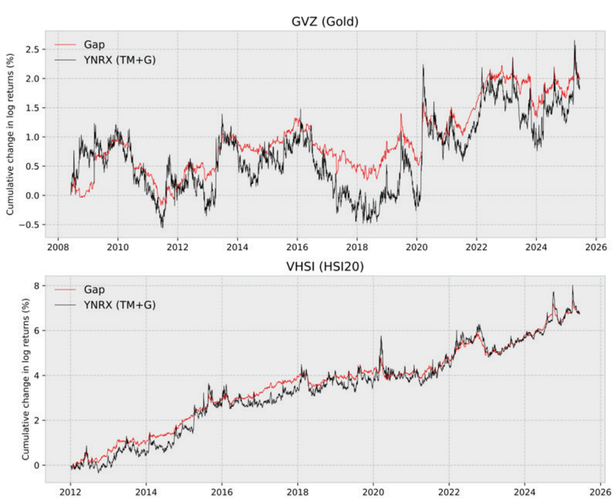
Although surprising in its results, the GSR Bands methodology has the drawback that, a priori, it is impossible to know in which band volatility will be curbed, and therefore where the market low will be. To try to mitigate this drawback, a complementary methodology to GSR Bands is presented below, which aims to reduce the number of bands plotted on an implied volatility index, using a formula based on the inequality of an asset's macrostructure. Below are the formulas for the equilibrium or macrostructure of an asset and market imbalance, the latter referred to as the YNRX model.

Tabla 3: GSR-MINI Band formulas

Description	Formula
Market balance	Total Market = Gap + Market
Market imbalance	YNRX 1 = Gap - Market YNRX 2 = Total Market + Gap YNRX 3 = Total Market + Market

Taking these formulas into account, we now present the graphs of the Gap component and the YNRX (TM+G) model for the cases of the implied volatility indices of Gold (GVZ) and HSI20 (VHSI). In both cases, we can see how the opening gap and its smooth trend serve as a kind of resistance to the YNRX (TM+G) model and its sawtooth trend, which can act as a potential detector of market lows.

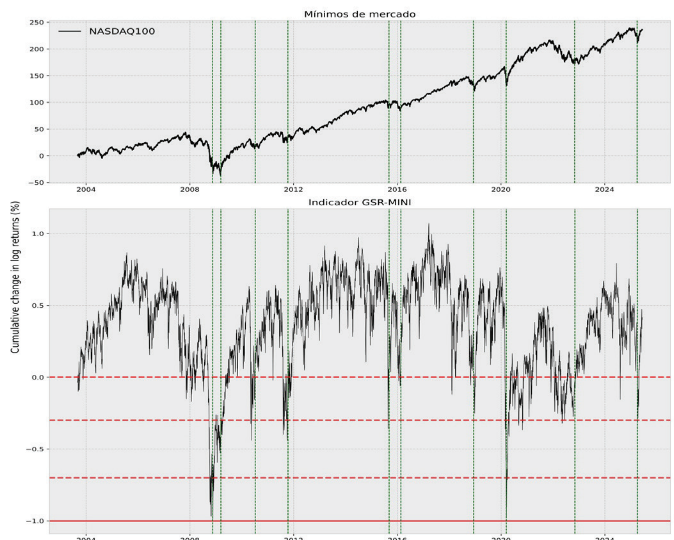
Figure 10: Gap and model YNRX 2 (TM+G) of the GVZ and VHSI



In the previous graphs, we can see how some, but not all, of the sawtooth patterns in the YNRX (TM+G) model bounce off the opening gap in their implied volatility index. Therefore, in order to see if these points correspond to actual market lows, we will now subtract both variables. Logically, if the YNRX variable (total market + gap) is subtracted from the gap variable, the result will be the total market of an implied volatility index with a negative sign. However, what interests us is to see those points where the subtraction takes a value of zero and check whether these correspond to a market low.

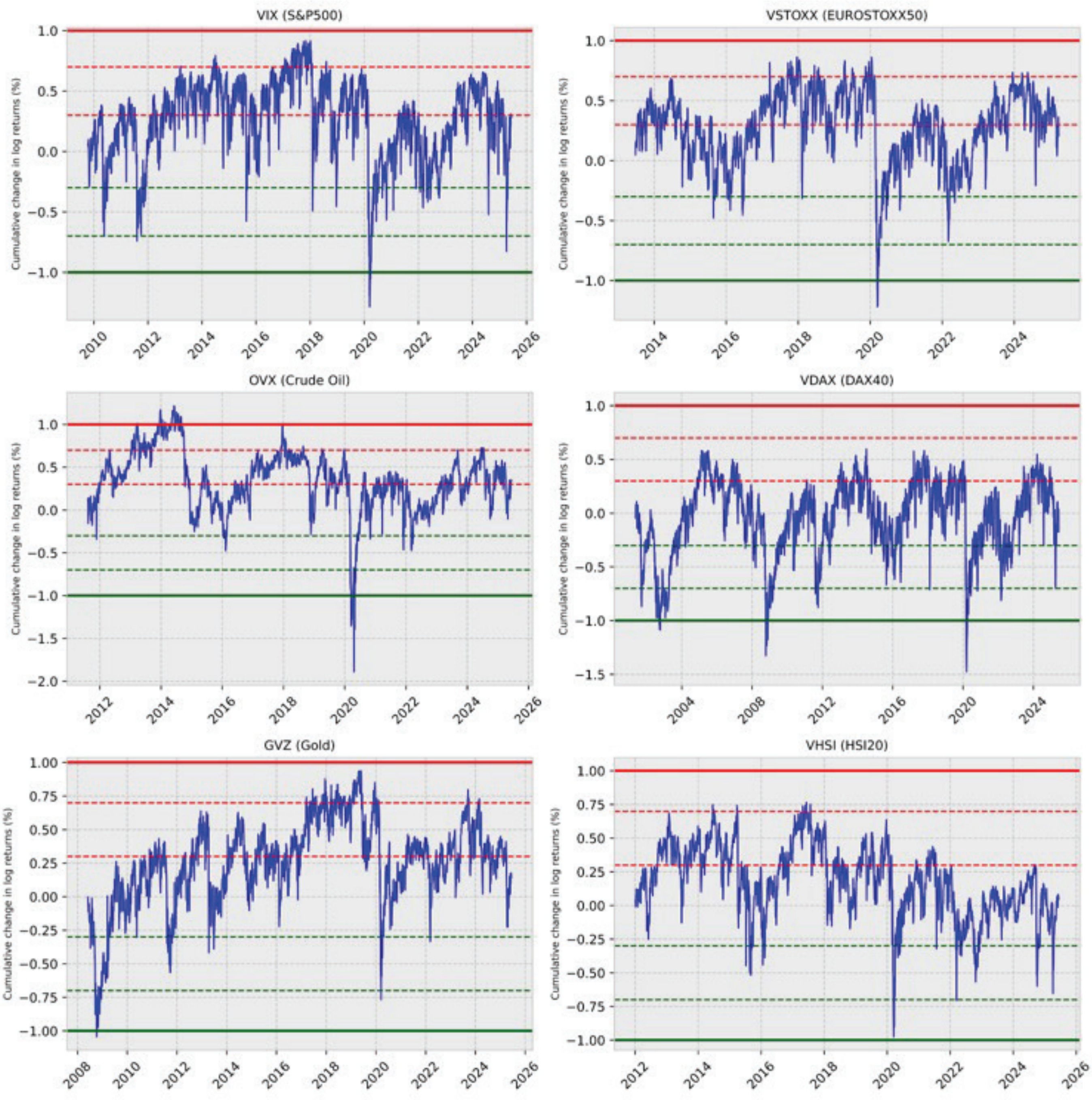
With this objective in mind, we proceed to perform this calculation for the VXN or implied volatility index of the NASDAQ100, and compare it with the NASDAQ100 future itself.

Figure 11: GSR-MINI Bands of the VXN (NASDAQ100)



Once the calculation has been made, it is clear that the GSR-MINI indicator applied to the NASDAQ100 implied volatility index not only reaches its minimum when the indicator value is zero, but market lows also occur when the GSR-MINI indicator reaches levels of -0.3 and -1. Given the curious nature of this fact, it is only necessary to verify that this same pattern occurs in the same way in other assets. To this end, the graphs of six implied volatility indices are presented below, including the VIX (S&P500), VSTOXX (EUROSTOXX50), VDAX NEW (DAX40), OVX (crude oil), GVZ (gold), and VHSI (HSI20).

Figure 12: GSR-MINI Bands for the VIX, VSTOXX, OVX, VDAX NEW, GVZ, and VHSI



After analyzing these six assets, it is confirmed that the values 0, -0.3, -0.7, and -1 act as points of maximum volatility and therefore market lows, highlighting that in the biggest market declines, the GSR-MINI indicator can fall below the value -1.

Conclusions

The graphical interpretation of the market as the sum of the gap and market component, or Macrostructure of an asset, allows for the addition of extra information to any financial analysis, representing a new application of technical analysis.

The seasonal behavior of the S&P500 can be understood through the seasonal behavior of the spot and futures of its implied volatility index or VIX. Since the seasonality of the opening gaps of the VIX spot and futures taking into account the Fibonacci series or prime numbers, they present the lows and highs of the seasonal behavior of the S&P500.

The ratio between the gap and market component of the spot and future VIX is a number very close to Phi. This, along with the use of the Fibonacci series and prime numbers in the rest of the analysis, highlights their influence on the stock market.

Volatility seems to fluctuate within a band formed by the opening gaps of the asset to which it belongs, acting as support or resistance for both volatility and traded volume, and which can mark the highs and lows of the S&P500.

The relationship between implied volatility of an asset and its opening gaps, taking into account the series of Fibonacci numbers and prime numbers or GSR Bands, is an effective methodology to detect total market lows. Representing price zones where the market has many possibilities to change its trend from bearish to bullish, although a priori we do not know in which gap band the price will turn. This methodology allows to create trading strategies, as it allows to detect market lows with an average of 9.6 days before they occur for the S&P500, DAX40 and Crude Oil and being able to detect 51.85% of them with only 0 or 1 days before the actual market lows.

GSR-MINI Bands greatly reduce the drawbacks of GSR Bands, in which there were a large number of bands where implied volatility peaked, and therefore where the market minimum occurred. In this sense, the GSR-MINI indicator limits the number of bands where volatility is most likely to peak to 3 or 4 points, corresponding to the values -0.3, -0.7, and -1.

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Serious Drawdowns in Trend-Following Strategies and Avoiding Them with Regime Switching Model

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Abstract

Though simple, trend-following has been widely identified as a strategy that can outperform market returns. However, the strategy comes with certain consequences, including relatively large losses known as drawdowns. Common and well-established recommendations for using this strategy involve keeping the amount allocated per trade small and diversifying trading across different markets to limit potential losses until the next profitable opportunity.

Although, since the year 2000, many asset classes have experienced larger drawdowns, accompanied by higher correlations among them. This has eroded diversification benefits, leading to total returns underperforming market returns for an extended period of time.

Studying historical returns from a trend-following strategy developed based on technical analysis suggests it exhibits alternating periods of effectiveness and ineffectiveness. Furthermore, these phases can sometimes cluster together, lasting for a certain period of time.

This thesis, according to the results of the simulations performed, proposes a method to exploit these change of phases. By employing a statistical technique called a "Regime Switching model," a trend following strategy would only be deployed when simulations indicate a greater than 50% chance of it being effective in the current phase. This approach has the potential to generate stable returns above market averages, and the model can be continuously updated as new data becomes available.

INTRODUCTION

1.1 Research Objective

Numerous textbooks on technical analysis highlight the superiority of "trend-following strategies" as investment tactics that can outperform the market[1].

Despite the claimed superiority of the strategies, it is inevitable that they experience significant losses from time to time. These losses are referred to as "drawdowns".

General textbooks on trend-following strategies suggest that minimizing drawdowns can be achieved by maintaining small position sizes, diversifying investments, and patiently waiting for the next uptrend, with numerous case studies support such approaches[2].

However, when examined using data from the year 2000 onwards, frequently observable are the cases of drawdown scale expansion, leading to prolonged periods where the total return of trend-following strategies significantly underperforms the market, resulting in unrecoverable losses.

Given these, it seems reasonable to avoid investing as much as possible during periods where significant drawdowns are likely to occur. Consequently, so that they can be avoided, developing a tool that predicts such drawdown cases, even if not perfectly, with a high degree of probability is desired.

This paper aims to propose one such a solution.

1.2. Overview

Based on the aforementioned research agenda, this paper addresses two primary objectives.

The first is to empirically verify whether trend-following strategies truly outperform the market by conducting data-driven simulations.

While existing literature on trend-following strategies primarily relies on empirical analyses using data in the 10-year stretch, from the mid-1990s to the mid-2000s, this paper re-examines the performance of the strategies using data from the early 2000s to the present, spanning nearly 25 years.

The second objective is to investigate how to effectively avoid pending drawdowns.

Before delving into this, however, it is essential to highlight an empirical observation.

A detailed time series analysis of the returns generated by trend-following strategies based on technical indicators reveals a clear pattern of alternating periods where trend-following strategies are either effective or ineffective. Moreover, these periods tend to persist for a certain duration, exhibiting a clustering phenomenon.

In order to exploit this characteristic, a regime-switching model, a quantitative econometric technique[3], was employed in this paper to determine the attribution of a pending period. The model provides a specific probability, based on a trend-following strategy, of a pending as to which of the two regimes it will belong to.

Based on this, it was hypothesized and empirically tested that by applying the trend-following strategy only when the probability is more than 50% for earning excess returns, it could consistently outperform the market.

Given regime-switching models can iteratively be updated and be recalculated with each new data point, it was expected that if the model were to demonstrate robust performance, it could serve as a valuable adjunct to traditional technical analysis.

While regime-switching models find frequent application in the fields of economics and finance, the combination of such models with technical analysis is, to the best of my knowledge, a relatively novel approach.

DATA AND METHODS

2.1. Data

The data used in this study consisted of weekly four-bar data for

18 price indices: 6 each for equities, currencies, and commodities (18 = 6 x 3).

The sample period was from the first week of November 2001 to the second week of May 2024.

More specifically, for equities, there are 6 indices representing major stock markets in developed and emerging economies: Nikkei 225, Dow Jones Industrial Average, Nasdaq Composite, Euro Stoxx 50, Shanghai Composite Index, Nifty 50.

Regarding currencies, there are 6 currency pairs against the Japanese yen, which are frequently traded by Japanese investors: USD/JPY, AUD/JPY, NZD/JPY, ZAR/JPY, CAD/JPY, and as the major currency pair EUR/USD.

For commodities, there are 6 indices and the selection was, in addition to their representative nature in commodity markets, based on the availability of continuous data during the sample period: Coffee, WTI Crude Oil (WTI), Gold, Copper, Wheat, and Corn.

All data were obtained and downloaded from Yahoo Finance US.

2.2. Method

2.2.1. About Trend Follow Strategies

For the analytical methodology employed in this study, it started with calculating a series of returns for a trend-following strategy based on the weekly four-bar data. The outline is as follows:

Step1: Compute 11 trend-following technical indicators from the data collected and generate buy and sell signals which are expressed as binary values (1 for a buy signal and 0 for a sell signal) determined by predefined logical expressions.

Step2: Based on the buy/sell signals generated in Step1 above, execute trades at the beginning of the following week. Specifically, if a buy signal is triggered in week t, we purchase the corresponding price index at the opening price of week t+1. Conversely, if a sell signal is triggered in week t, and if there is an existing long position, the position is liquidated at the opening price of week t+1.

And for simplicity, dividend payments in equities as such were not considered in this analysis.

Consequently, the return for the asset actually purchased in week t+1 is calculated as the percentage change from the opening price to the closing price of week t+1.

If buy signals persist beyond week t+1, subsequent returns are calculated as the percentage change from the previous week's closing price to the current (relevant) week's closing price.

Conversely, if a sell signal is triggered in week t, the return for week t+1 is zero.

The return for week t is calculated as the percentage change from the opening price of week t to the opening price of week t+1.

It's important to note that this study exclusively considers long positions and does not engage in short selling. Therefore, after selling, the portfolio holds only cash, and the return remains zero until the next purchase opportunity.

Step3: To construct a trend-following strategy, 11 of standard technical indicators commonly used for trend analysis were selected, those are Heikinashi, Moving Average (two variations are considered: Moving Average 1 and Moving Average 2)[4], Bollinger Bands, Keltner Channels, Donchian Channels, MACD, Three Line Break, Parabolic SAR, DMI and Ichimoku[5].

2.2.2. About Regime-Switching Model

As mentioned, a regime-switching model is applied in this paper for the purpose of enhancing the performance of trend-following strategies. Specifically, among various regime-switching models, the Hidden Markov Model (HMM) is applied in this study.

The outline of application of HMM is as follows:

Step1: The series of returns from the trend-following strategy calculated in section 2.2.1 was expressed in using a "Factor Model"[6].

Specifically, it was assumed that a linear regression model with the return series of the trend-following strategy as the dependent variable while the returns of benchmark price indices as independent variables.

In the actual estimation, however, it used the natural logarithm of cumulative returns starting from the first week of November 2001 as the return series.

Applying the factor model implies that the returns of the trend-following strategy from each of the price index were generated by two factors: α (excess returns generated independently of the returns of each price index) and β (sensitivity to the fluctuations in the returns of each price index).

Step2: HMM was applied to the factor model estimated in Step1.

Although HMM estimation can be programed with such programming software as R, EViews, which is the procedure in the commercial econometric software package, was conveniently used for this study. Because by specifying the variable names for the explanatory and dependent variables, estimating the HMM was relatively easy with this procedure in EViews.

In order to improve the returns of the trend-following strategy using the estimated HMM, different parameters (α and β) were estimated for two regimes (an "uptrend phase" and a "downtrend phase") for the HMM in this paper.

Additionally, the "regime transition probability" was estimated[7] at each time point. This probability represents the likelihood (in percentage) of a specific period (e.g., the second week of April) being an uptrend or downtrend phase during the analysis period (e.g., "73% probability of being an uptrend phase"). If this probability were reliable, it could be expected to improve the returns of the trend-following strategy by buying during uptrend phases and selling during downtrend phases, which is the core idea of this paper.

Using the estimated HMM, it is possible to forecast the regime transition probability for week t+1 based on data up to week t.

Therefore, in this paper, the established trading rule was as follows: if the expected value of the regime transition probability for week t+1 in week t exceeded 50%, purchase the corresponding asset at the opening price of week t+1. Conversely, if the expected value was below 50% and if there were any existing long positions, sell them at the opening price of week t+1.

2.3. Evaluation

The data used for performance evaluation consists of the returns of each asset class: the returns based on the trend-following strategy, and the returns based on the HMM.

Performance evaluation was conducted using the risk-adjusted return, calculated by dividing the mean return by the standard deviation. Specifically, the performance of the HMM-based trend-following strategy was evaluated by comparing its risk-adjusted return to that of the benchmark asset class.

RESULTS

3.1. Performance on Trend Follow Strategies

As shown in Table 1, out of the 198 (18 x 11) combinations, only 89, or only 45%, outperformed the respective asset classes in terms of risk-adjusted average returns.

Assuming 11 technical indicators commonly used in trend analysis were applied to each of the 6 price indices in equities, currencies, and commodities (6 x 3 =18 in total) in a trading strategy based on the buy/sell signals generated by these technical indicators, the risk-adjusted average returns were found to be lower than those of the respective asset classes in most cases (Table 2).

This implies that less than half of the trend-following strategies based on technical indicators outperformed the underlying asset classes during the sample period (November 2001 - May 2024), suggesting the performance of trend-following strategies using technical indicators was not particularly favorable over the period.

Incidentally, Figure 1 depicts the cumulative returns of the Nikkei 225, USD/JPY and copper as representative price indices for equities, currencies, and commodities, respectively. It can be observed that the number of trend-following strategies that outperformed the cumulative returns of each price index was extremely limited, suggesting the superiority of trend-following strategies themselves couldn't be confirmed.

Table1 Performance on Trend-following Strategies

	Index	Trend-follow Strategies
Heikinashi	12	6
MA (Moving Average) 1	10	8
MA (Moving Average) 2	11	7
Bollinger Band	2	16
Keltner Channel	12	6
Donchian Channel	15	3
MACD	10	8
Three Line Break	12	6
Parabolic SAR	9	9
Ichimoku	10	8
DMI	6	12
Total	109	89

Note: Each number is the number of strategies outperformed.

Table2 Risk-adjusted Excess returns with Trend-following Strategies

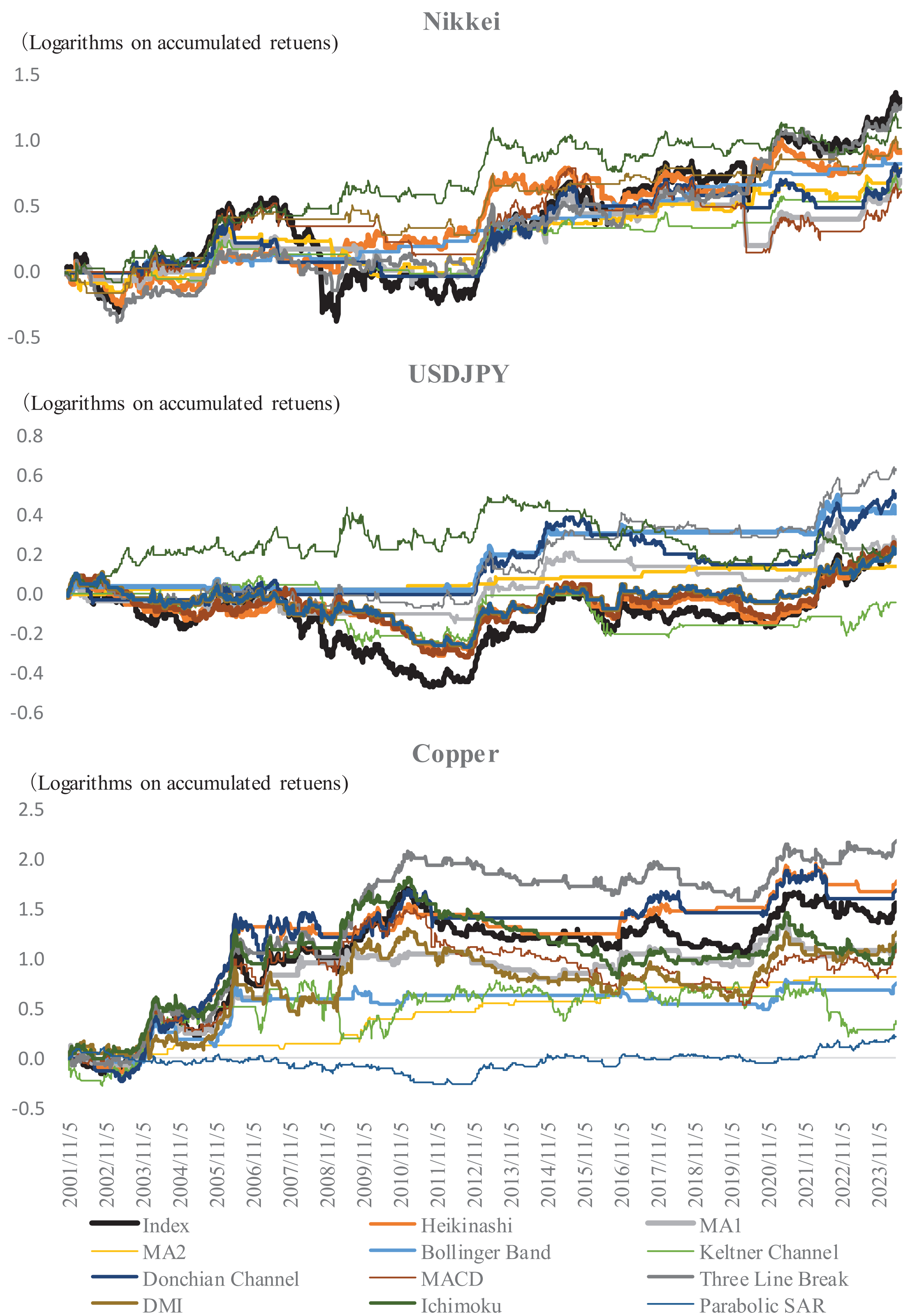
Heikinnashi			MA1			MA2			Bollinger Band		
Equities	Nikkei	▲ 0.002	Equities	Nikkei	▲ 0.010	Equities	Nikkei	0.005	Equities	Nikkei	0.054
	Dow Industrial	▲ 0.007		Dow Industrial	▲ 0.018		Dow Industrial	▲ 0.046		Dow Industrial	0.019
	Nasdaq Composit	▲ 0.007		Nasdaq Composit	▲ 0.006		Nasdaq Composit	▲ 0.017		Nasdaq Composit	0.030
	EuroStoxx	▲ 0.049		EuroStoxx	0.012		EuroStoxx	▲ 0.017		EuroStoxx	0.070
	Shanghi Composit	0.025		Shanghi Composit	0.038		Shanghi Composit	0.059		Shanghi Composit	0.064
	Nifty50	0.084		Nifty50	▲ 0.045		Nifty50	▲ 0.011		Nifty50	▲ 0.034
Currencies	USDJPY	0.006	Currencies	USDJPY	0.013	Currencies	USDJPY	0.030	Currencies	USDJPY	0.046
	AUDJPY	▲ 0.011		AUDJPY	▲ 0.009		AUDJPY	▲ 0.006		AUDJPY	0.075
	NZDJPY	▲ 0.027		NZDJPY	▲ 0.013		NZDJPY	▲ 0.030		NZDJPY	0.020
	ZARJPY	▲ 0.047		ZARJPY	0.005		ZARJPY	0.004		ZARJPY	0.081
	CADJPY	▲ 0.014		CADJPY	▲ 0.012		CADJPY	0.023		CADJPY	0.061
	EURUSD	▲ 0.015		EURUSD	0.006		EURUSD	▲ 0.010		EURUSD	0.078
Commodities	Coffee	0.106	Commodities	Coffee	0.002	Commodities	Coffee	▲ 0.009	Commodities	Coffee	▲ 0.009
	Copper	▲ 0.001		Copper	0.013		Copper	▲ 0.003		Copper	0.032
	Gold	▲ 0.037		Gold	▲ 0.000		Gold	▲ 0.077		Gold	0.046
	WTI	0.002		WTI	▲ 0.003		WTI	▲ 0.007		WTI	0.055
	Corn	▲ 0.005		Corn	▲ 0.030		Corn	0.014		Corn	0.077
	Wheat	0.055		Wheat	0.033		Wheat	0.019		Wheat	0.019

Keltner Channel			Donchian Channel			MACD			Three Line Break		
Equities	Nikkei	0.003	Equities	Nikkei	▲ 0.004	Equities	Nikkei	▲ 0.004	Equities	Nikkei	0.014
	Dow Industrial	▲ 0.044		Dow Industrial	0.002		Dow Industrial	0.002		Dow Industrial	0.002
	Nasdaq Composit	▲ 0.092		Nasdaq Composit	▲ 0.005		Nasdaq Composit	▲ 0.005		Nasdaq Composit	▲ 0.004
	EuroStoxx	▲ 0.064		EuroStoxx	▲ 0.006		EuroStoxx	▲ 0.006		EuroStoxx	▲ 0.023
	Shanghi Composit	0.073		Shanghi Composit	0.005		Shanghi Composit	0.005		Shanghi Composit	0.014
	Nifty50	0.006		Nifty50	▲ 0.041		Nifty50	▲ 0.041		Nifty50	▲ 0.049
Currencies	USDJPY	0.049	Currencies	USDJPY	▲ 0.020	Currencies	USDJPY	0.032	Currencies	USDJPY	0.008
	AUDJPY	▲ 0.056		AUDJPY	▲ 0.042		AUDJPY	▲ 0.008		AUDJPY	▲ 0.016
	NZDJPY	▲ 0.044		NZDJPY	▲ 0.015		NZDJPY	0.007		NZDJPY	▲ 0.019
	ZARJPY	▲ 0.023		ZARJPY	0.008		ZARJPY	▲ 0.005		ZARJPY	0.003
	CADJPY	▲ 0.021		CADJPY	▲ 0.032		CADJPY	0.000		CADJPY	▲ 0.015
	EURUSD	▲ 0.029		EURUSD	▲ 0.057		EURUSD	0.024		EURUSD	▲ 0.016
Commodities	Coffee	▲ 0.020	Commodities	Coffee	▲ 0.014	Commodities	Coffee	▲ 0.024	Commodities	Coffee	▲ 0.043
	Copper	▲ 0.037		Copper	▲ 0.024		Copper	0.003		Copper	▲ 0.016
	Gold	▲ 0.072		Gold	▲ 0.028		Gold	0.002		Gold	▲ 0.031
	WTI	▲ 0.021		WTI	▲ 0.050		WTI	▲ 0.022		WTI	▲ 0.031
	Corn	0.010		Corn	▲ 0.010		Corn	▲ 0.016		Corn	▲ 0.011
	Wheat	0.028		Wheat	▲ 0.008		Wheat	▲ 0.006		Wheat	0.016

Parabolic SAR			Ichimoku			DMI			(Ref: risk adjusted return)		
Equities	Nikkei	▲ 0.000	Equities	Nikkei	0.011	Equities	Nikkei	0.017	Equities	Nikkei	0.077
	Dow Industrial	▲ 0.009		Dow Industrial	▲ 0.013		Dow Industrial	▲ 0.010		Dow Industrial	0.098
	Nasdaq Composit	▲ 0.014		Nasdaq Composit	▲ 0.020		Nasdaq Composit	▲ 0.032		Nasdaq Composit	0.116
	EuroStoxx	▲ 0.023		EuroStoxx	▲ 0.029		EuroStoxx	▲ 0.009		EuroStoxx	0.039
	Shanghi Composit	0.020		Shanghi Composit	0.067		Shanghi Composit	0.042		Shanghi Composit	0.012
	Nifty50	0.093		Nifty50	0.044		Nifty50	0.086		Nifty50	0.093
Currencies	USDJPY	0.002	Currencies	USDJPY	0.010	Currencies	USDJPY	0.040	Currencies	USDJPY	0.063
	AUDJPY	▲ 0.004		AUDJPY	▲ 0.008		AUDJPY	0.014		AUDJPY	0.026
	NZDJPY	▲ 0.034		NZDJPY	0.001		NZDJPY	0.005		NZDJPY	0.037
	ZARJPY	0.008		ZARJPY	▲ 0.022		ZARJPY	0.009		ZARJPY	▲ 0.012
	CADJPY	▲ 0.024		CADJPY	▲ 0.007		CADJPY	▲ 0.013		CADJPY	0.030
	EURUSD	0.088		EURUSD	▲ 0.003		EURUSD	0.072		EURUSD	0.030
Commodities	Coffee	0.082	Commodities	Coffee	▲ 0.011	Commodities	Coffee	0.051	Commodities	Coffee	0.036
	Copper	▲ 0.001		Copper	▲ 0.014		Copper	0.020		Copper	0.029
	Gold	▲ 0.029		Gold	▲ 0.002		Gold	▲ 0.031		Gold	0.059
	WTI	0.007		WTI	0.005		WTI	▲ 0.026		WTI	0.026
	Corn	0.024		Corn	0.004		Corn	0.012		Corn	0.021
	Wheat	0.067		Wheat	0.012		Wheat	0.068		Wheat	0.041

Note1 : Calculated with weekly return average after risk adjusted (%)
Note2 : Weekly return average after risk adjusted is difference between average return on trend-follow strategy and weekly average return of price index (%)

Figure1 Accumulative Returns of Trend-following Strategies: Nikkei, USDJPY, Copper



3.2. Applying HMM and Improving Performance

One possible reason for the underperformance of trend-following strategies is that the buy/sell signals generated by the technical indicators used in these strategies may not have managed to distinguish uptrends from downtrends, or vice versa.

To address this issue, a Hidden Markov Model (HMM) was applied in the process.

As explained in Section 2, the return series of each trend-following strategy is represented by using a factor model that explains the returns with the returns of each price index and a constant term, and a HMM is applied to this factor model, assuming that the factor model has different parameters (α, β) in each of the two regimes: "uptrend" and "downtrend".

In this HMM, it is interpreted that the higher the probability of being in an uptrend, the higher the likelihood of obtaining a positive return. Therefore, the idea of this paper is buying when the probability of being in an uptrend exceeds 50% and selling when it falls below 50%, in order to outperform the returns of each price index.

According to Table 3, out of the 198 (18 x 11) combinations, 124, or 62.6%, outperformed the respective asset class in terms of risk-adjusted average returns by using HMM. And the price index itself achieved the highest performance in 33 cases, and the trend-following strategy achieved the highest performance in 41 cases.

Table3 Performance on Trend-following Strategy when HMM is applied

	Index	Trend-follow Strategies	HMM
Heikinashi	2	3	13
MA1	2	1	15
MA2	3	3	12
Bollinger	1	10	7
Keltner Channel	3	3	12
Donchain Channel	5	1	12
MACD	4	3	11
Three Line Break	4	0	14
Parabolic SAR	2	4	12
Ichimoku	5	4	9
DMI	2	9	7
Total	33	41	124

Note: Each number is the number of strategies outperformed.

Table 4 Risk-adjusted Excees returns with Trend-following Starategies and HMM

Heikinashi

		Trend-follow	HMM
Equities	Nikkei	▲ 0.002	0.013
	Dow Industrial	▲ 0.007	0.020
	Nasdaq Composite	▲ 0.007	0.002
	EuroStoxx	▲ 0.049	0.020
	Shanghi Composite	0.025	0.036
	Nifty50	0.084	▲ 0.013
Currencies	USDJPY	0.006	0.033
	AUSJPY	▲ 0.011	0.001
	NZDJPY	▲ 0.027	▲ 0.001
	ZARJPY	▲ 0.047	0.047
	CANJPY	▲ 0.014	0.016
	EURUSD	▲ 0.015	0.024
Commodities	Coffee	0.106	▲ 0.025
	Copper	▲ 0.001	0.084
	Gold	▲ 0.037	0.026
	WTI	0.002	0.017
	Corn	▲ 0.005	▲ 0.001
	Wheat	0.055	0.029

MA1

		Trend-follow	HMM
Equities	Nikkei	▲ 0.010	0.005
	Dow Industrial	▲ 0.018	▲ 0.004
	Nasdaq Composite	▲ 0.006	0.012
	EuroStoxx	0.012	0.036
	Shanghi Composite	0.038	0.041
	Nifty50	▲ 0.045	0.011
Currencies	USDJPY	0.013	0.022
	AUSJPY	▲ 0.009	0.025
	NZDJPY	▲ 0.013	0.032
	ZARJPY	0.005	0.025
	CANJPY	▲ 0.012	0.006
	EURUSD	0.006	0.007
Commodities	Coffee	0.002	0.034
	Copper	0.013	0.088
	Gold	▲ 0.000	0.011
	WTI	▲ 0.003	▲ 0.003
	Corn	▲ 0.030	0.023
	Wheat	0.033	0.027

MA2

		Trend-follow	HMM
Equities	Nikkei	0.005	0.012
	Dow Industrial	▲ 0.046	0.041
	Nasdaq Composite	▲ 0.017	0.010
	EuroStoxx	▲ 0.017	0.020
	Shanghi Composite	0.059	0.026
	Nifty50	▲ 0.011	▲ 0.003
Currencies	USDJPY	0.030	0.032
	AUSJPY	▲ 0.006	0.013
	NZDJPY	▲ 0.030	0.014
	ZARJPY	0.004	0.058
	CANJPY	0.023	0.006
	EURUSD	▲ 0.010	0.009
Commodities	Coffee	▲ 0.009	▲ 0.012
	Copper	▲ 0.003	0.101
	Gold	▲ 0.077	▲ 0.015
	WTI	▲ 0.007	0.001
	Corn	0.014	0.016
	Wheat	0.019	▲ 0.005

Bollinger Band

		Trend-follow	HMM
Equities	Nikkei	0.054	0.060
	Dow Industrial	0.019	0.017
	Nasdaq Composite	0.030	▲ 0.001
	EuroStoxx	0.070	0.075
	Shanghi Composite	0.064	0.027
	Nifty50	▲ 0.034	0.038
Currencies	USDJPY	0.046	0.040
	AUSJPY	0.075	0.007
	NZDJPY	0.020	0.037
	ZARJPY	0.081	0.020
	CANJPY	0.061	▲ 0.000
	EURUSD	0.078	0.081
Commodities	Coffee	▲ 0.009	▲ 0.022
	Copper	0.032	0.084
	Gold	0.046	0.004
	WTI	0.055	▲ 0.011
	Corn	0.077	0.001
	Wheat	0.019	0.040

Keltner Channel

		Trend-follow	HMM
Equities	Nikkei	0.003	0.010
	Dow Industrial	▲ 0.044	▲ 0.003
	Nasdaq Composite	▲ 0.092	▲ 0.001
	EuroStoxx	▲ 0.064	0.006
	Shanghi Composite	0.073	0.003
	Nifty50	0.006	0.007
Currencies	USDJPY	0.049	0.017
	AUSJPY	▲ 0.056	0.020
	NZDJPY	▲ 0.044	▲ 0.001
	ZARJPY	▲ 0.023	0.019
	CANJPY	▲ 0.021	0.021
	EURUSD	▲ 0.029	0.029
Commodities	Coffee	▲ 0.020	0.038
	Copper	▲ 0.037	0.117
	Gold	▲ 0.072	0.022
	WTI	▲ 0.021	0.002
	Corn	0.010	0.002
	Wheat	0.028	0.006

Donchian Channel

		Trend-follow	HMM
Equities	Nikkei	▲ 0.004	▲ 0.001
	Dow Industrial	0.002	▲ 0.001
	Nasdaq Composite	▲ 0.005	▲ 0.001
	EuroStoxx	▲ 0.006	0.022
	Shanghi Composite	0.005	0.013
	Nifty50	▲ 0.041	0.034
Currencies	USDJPY	▲ 0.020	0.014
	AUSJPY	▲ 0.042	0.022
	NZDJPY	▲ 0.015	0.007
	ZARJPY	0.008	0.029
	CANJPY	▲ 0.032	0.012
	EURUSD	▲ 0.057	▲ 0.011
Commodities	Coffee	▲ 0.014	▲ 0.002
	Copper	▲ 0.024	0.075
	Gold	▲ 0.028	▲ 0.005
	WTI	▲ 0.050	0.029
	Corn	▲ 0.010	0.011
	Wheat	▲ 0.008	0.038

Table 4 Risk-adjusted Excees returns with Trend-following Starategies and HMM(Continued)

MACD

		Trend-follow	HMM
Equities	Nikkei	▲ 0.004	▲ 0.001
	Dow Industrial	0.002	▲ 0.001
	Nasdaq Composite	▲ 0.005	▲ 0.001
	EuroStoxx	▲ 0.006	0.022
	Shanghi Composite	0.005	0.013
	Nifty50	▲ 0.041	0.034
Currencies	USDJPY	0.032	0.041
	AUSJPY	▲ 0.008	▲ 0.000
	NZDJPY	0.007	0.023
	ZARJPY	▲ 0.005	0.050
	CANJPY	0.000	0.003
	EURUSD	0.024	0.027
Commodities	Coffee	▲ 0.024	0.019
	Copper	0.003	0.168
	Gold	0.002	▲ 0.010
	WTI	▲ 0.022	0.004
	Corn	▲ 0.016	0.002
	Wheat	▲ 0.006	▲ 0.007

Three Line Break

		Trend-follow	HMM
Equities	Nikkei	0.014	0.017
	Dow Industrial	0.002	0.020
	Nasdaq Composite	▲ 0.004	0.002
	EuroStoxx	▲ 0.023	0.024
	Shanghi Composite	0.014	0.032
	Nifty50	▲ 0.049	0.007
Currencies	USDJPY	0.008	0.021
	AUSJPY	▲ 0.016	0.012
	NZDJPY	▲ 0.019	▲ 0.000
	ZARJPY	0.003	0.010
	CANJPY	▲ 0.015	▲ 0.018
	EURUSD	▲ 0.016	0.044
Commodities	Coffee	▲ 0.043	0.027
	Copper	▲ 0.016	0.097
	Gold	▲ 0.031	▲ 0.021
	WTI	▲ 0.031	▲ 0.001
	Corn	▲ 0.011	0.009
	Wheat	0.016	0.023

Parabolic SAR

		Trend-follow	HMM
Equities	Nikkei	▲ 0.000	0.012
	Dow Industrial	▲ 0.009	0.002
	Nasdaq Composite	▲ 0.014	▲ 0.009
	EuroStoxx	▲ 0.023	0.014
	Shanghi Composite	0.020	0.004
	Nifty50	0.093	0.168
Currencies	USDJPY	0.002	0.012
	AUSJPY	▲ 0.004	0.025
	NZDJPY	▲ 0.034	0.026
	ZARJPY	0.008	0.017
	CANJPY	▲ 0.024	0.003
	EURUSD	0.088	0.018
Commodities	Coffee	0.082	▲ 0.007
	Copper	▲ 0.001	0.015
	Gold	▲ 0.029	▲ 0.008
	WTI	0.007	0.017
	Corn	0.024	0.001
	Wheat	0.067	0.091

Ichimoku

		Trend-follow	HMM
Equities	Nikkei	0.011	0.017
	Dow Industrial	▲ 0.013	0.019
	Nasdaq Composite	▲ 0.020	▲ 0.002
	EuroStoxx	▲ 0.029	0.046
	Shanghi Composite	0.067	0.012
	Nifty50	0.044	▲ 0.014
Currencies	USDJPY	0.010	0.041
	AUSJPY	▲ 0.008	▲ 0.010
	NZDJPY	0.001	▲ 0.009
	ZARJPY	▲ 0.022	0.007
	CANJPY	▲ 0.007	0.018
	EURUSD	▲ 0.003	0.007
Commodities	Coffee	▲ 0.011	▲ 0.007
	Copper	▲ 0.014	▲ 0.001
	Gold	▲ 0.002	▲ 0.011
	WTI	0.005	0.018
	Corn	0.004	▲ 0.014
	Wheat	0.012	0.017

DMI

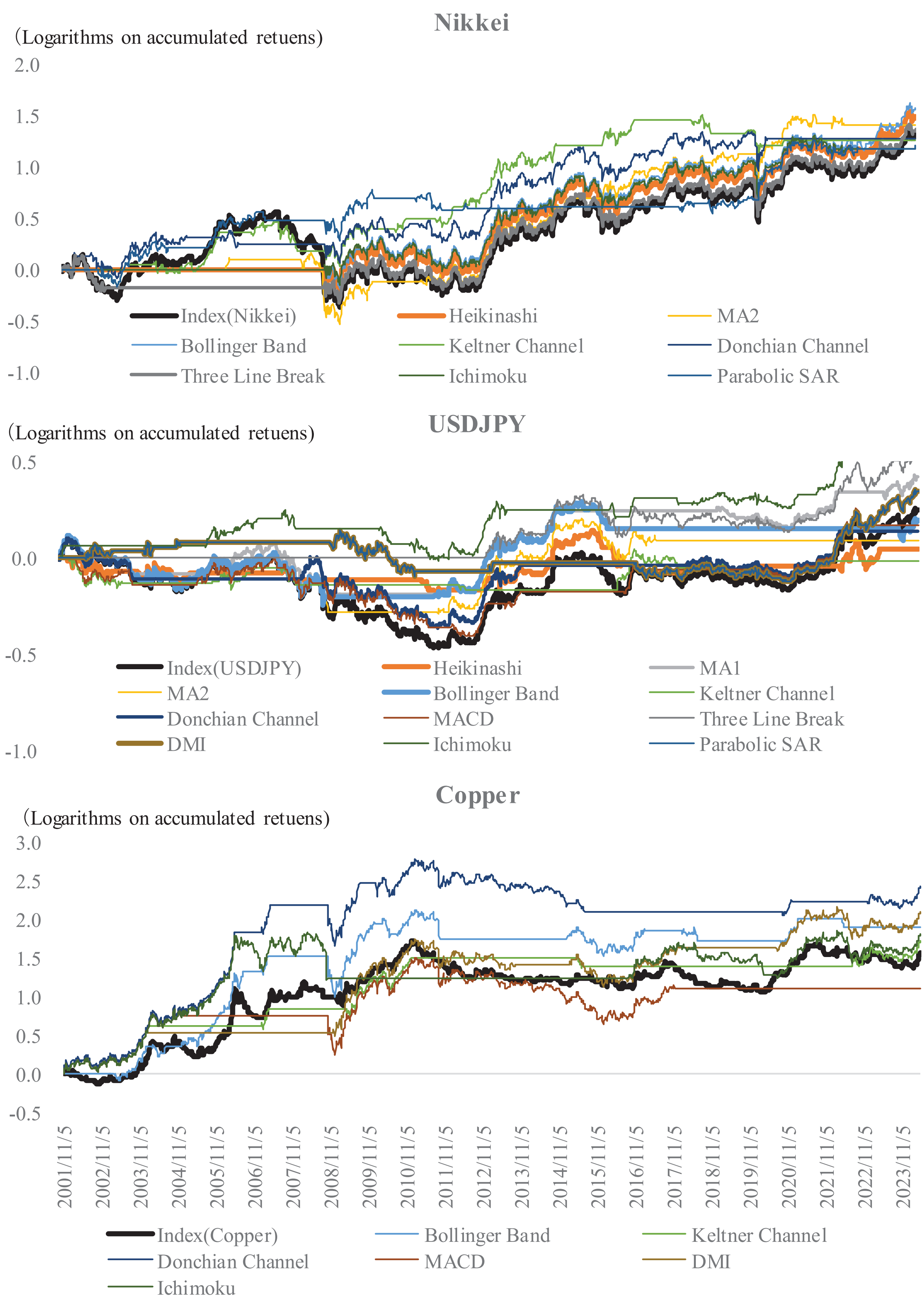
		Trend-follow	HMM
Equities	Nikkei	0.017	▲ 0.003
	Dow Industrial	▲ 0.010	▲ 0.018
	Nasdaq Composite	▲ 0.032	▲ 0.025
	EuroStoxx	▲ 0.009	0.021
	Shanghi Composite	0.042	0.020
	Nifty50	0.086	0.009
Currencies	USDJPY	0.040	0.035
	AUSJPY	0.014	0.027
	NZDJPY	0.005	0.001
	ZARJPY	0.009	0.015
	CANJPY	▲ 0.013	0.027
	EURUSD	0.072	0.076
Commodities	Coffee	0.051	▲ 0.002
	Copper	0.020	▲ 0.021
	Gold	▲ 0.031	0.011
	WTI	▲ 0.026	0.019
	Corn	0.012	0.000
	Wheat	0.068	0.009

(Ref: risk adjusted return)

Equities	Nikkei	0.077
	Dow Industrial	0.098
	Nasdaq Composite	0.116
	EuroStoxx	0.039
	Shanghi Composite	0.012
	Nifty50	0.093
Currencies	USDJPY	0.063
	AUSJPY	0.026
	NZDJPY	0.037
	ZARJPY	▲ 0.012
	CANJPY	0.030
	EURUSD	0.030
Commodities	Coffee	0.036
	Copper	0.029
	Gold	0.059
	WTI	0.026
	Corn	0.021
	Wheat	0.041

Note1 : Calculated with weekly return average after risk adjusted (%)
Note2 : weekly return average after risk adjusted is difference between average return on trend-follow strategy and weekly average return of price index (%)

Figure2. Accumulative Returns when HMM is applied Nikkei, USDJPY, Coper



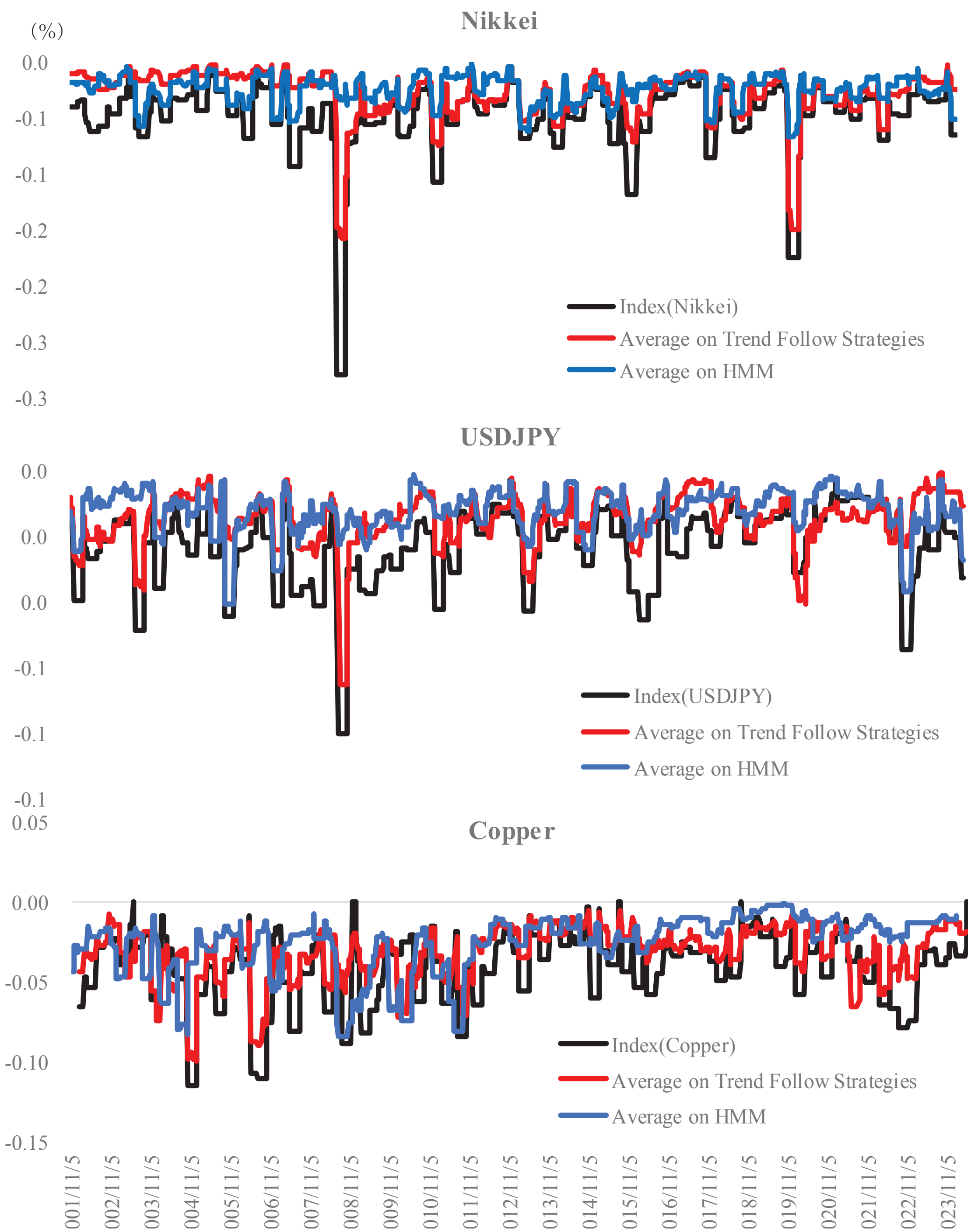
Based on these results, it can be concluded that applying an HMM to trend-following strategies did improve their performance.

Figure 2, the same as Figure 1, shows the cumulative returns of the Nikkei, USD/JPY and copper when the HMM was applied. It is evident that the performance was significantly improved.

Consequently, it can be concluded that applying an HMM to the returns of trend-following strategies significantly improved the superiority over the returns of asset classes.

3.3. Reducing Drawdowns

Figure3 Drowdowns: Nikkei, USDJPY, Copper



Note1 : Drowdown is the largest weekly loss (negative return) in 13 weeks.

Figure 3 plots the drawdowns when trend-following strategy and the HMM strategy (average values of 11 trend-following strategies were used for both) were applied on Nikkei, USD/JPY and copper as shown in Figures 1 and 2.

It is revealing that while the trend-following strategy does reduce drawdowns but is unable to avoid sharp drawdowns during market crashes. On the other hand, when the HMM was applied, it can be observed that, although not completely, the frequency increases in successfully avoiding sharp drawdowns.

DISCUSSIONS

Some additional insights into the results obtained in Section 3 are as follows.

In this study, a total of 198 return series were created by applying 11 technical indicators to each of the 18 price indices (6 for each of equities, currencies, and commodities).

For each of these 198 return-series, corresponding return series based on the HMM were calculated.

In examining all 198 trend-following strategies thus obtained, they can be classified into three categories:

1) Those where the underlying price index outperforms (meaning a buy-and-hold strategy starting from the purchase made from the first week of November 2001)
2) Those where the trend-following strategy outperforms
3) Those where the HMM outperforms.

What, then, are the factors that contribute to the differences in performance among these three categories?

Before proceeding, in this study, please recall that "the return series of each trend-following strategy expressed using a ‘factor model’ that explains the returns with the sensitivity of returns of each price index and a constant term."

It implies that the parameters α and α in the factor model, which represent the sources of return, may provide some insights. (Please refer to Appendix Table A for a list of the factor model parameters.)

4.1. Realizing “Factor Model” ～Relationship between α and β～

First, concerning the factor model prior to applying the HMM, the following points can be made (Figure 4):

1. Compared to the cases where the returns of the price index outperforming, the cases where the returns of the trend-following strategy itself is outperforming tends to have higher overall α values.

2. As for β, in the case of equities, a relationship can be found where the performance of the trend-following strategy is higher when β exceeds 1. However, there were no difference between the two when β was at or less than 1. Furthermore, for currencies and commodities, no relationship was found between the value of β and performance.

Figure4 Relationship between α and β under Factor model of Trend-follow Strategies: Equities, Currencies, Copper

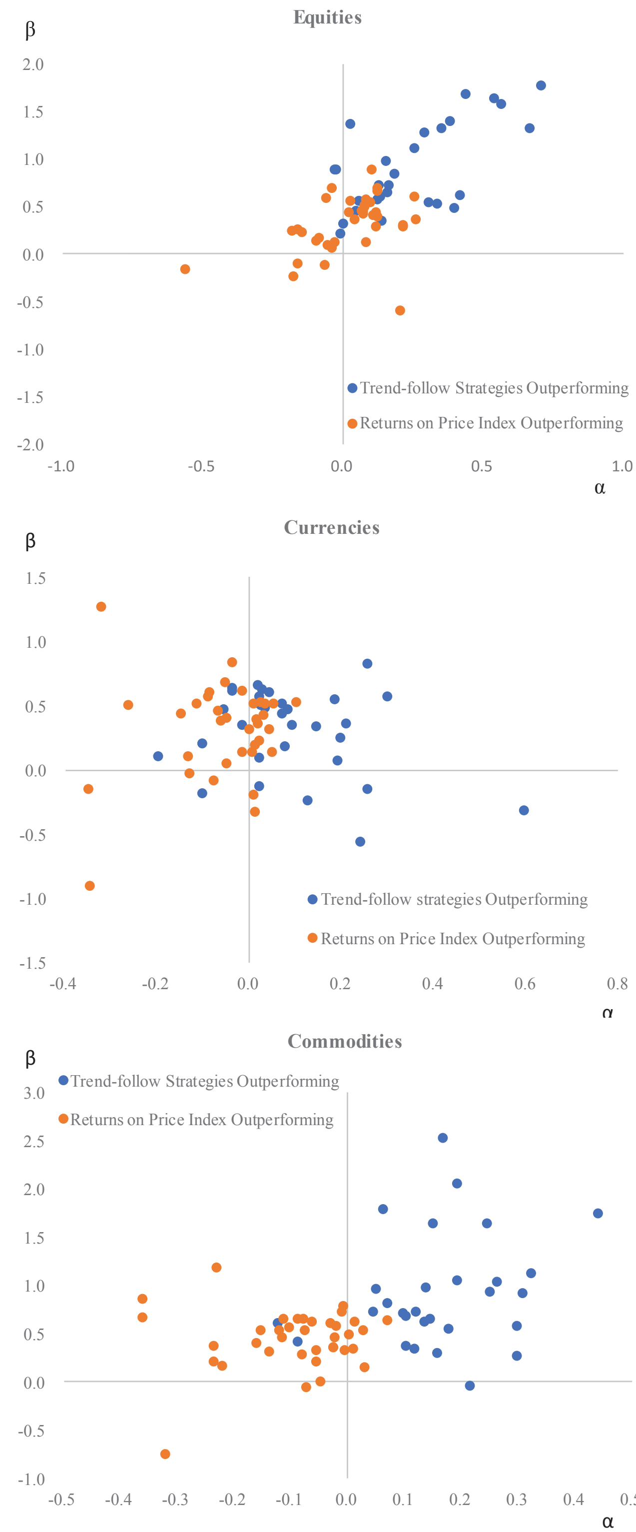
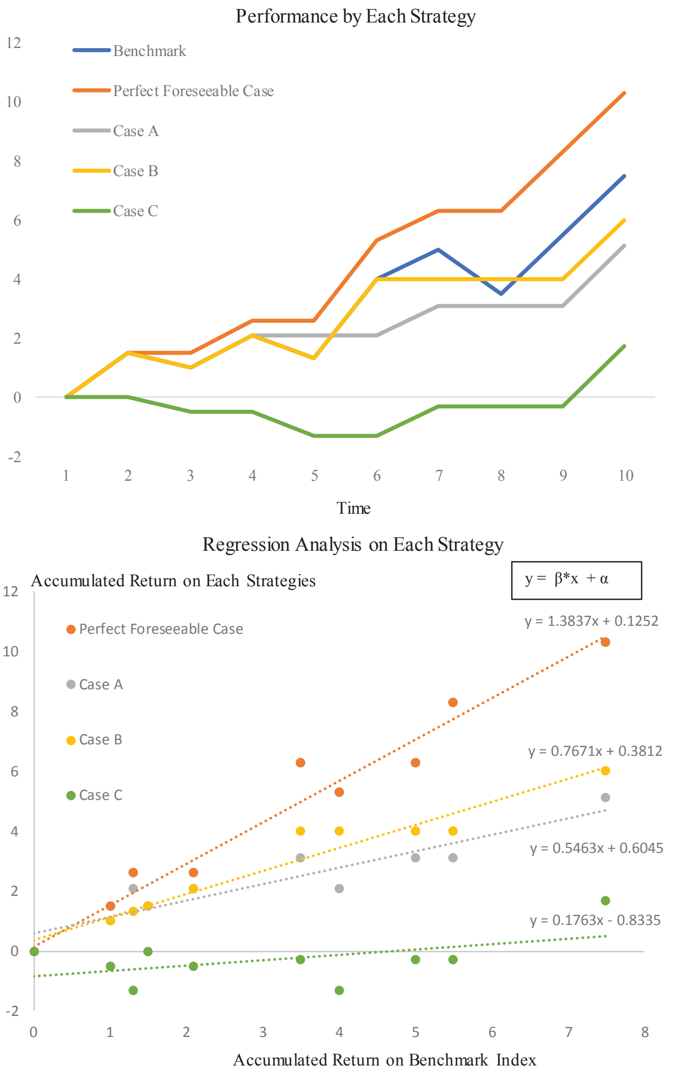


Figure5 Relatiohship between α and β under Factor Model: Hypothetical Example



In order to interpret these facts, let us first examine the relationship between the performance of a trend-following strategy and α and β, using a hypothetical example (Figure 5).

If a trend-following strategy successfully captures 100% of the downtrend phases of a price index (in “Perfect Foreseeable” Case in Figure5), the cumulative return will be flat during these downtrend phases, and thus, β will generally exceed the benchmark and β > 1.

Next, if the strategy captures downtrend phases less perfectly, the cumulative return will remain positive, and higher the imperfection and lower the capture frequency, the value of β declines to below 1, while the value of α is positive (cases A and B in Figure 5).

However, if the strategy captures very few uptrend phases but captures a few sharp uptrend movements, resulting in a positive cumulative return, it is possible to have a combination of a positive β below 1 and a negative α (case C in Figure 5).

Based on the hypothetical examples, the results of the factor model can be interpreted as follows:

Many trend-following strategies that outperform the benchmark price index do so not by perfectly capturing the trends of the price index, but rather by compensating for it with a positive α. However, it is also worth noting that there are cases, such as case C in Figure 5, where the strategy outperforms with a combination of a β less than 1 and a negative α.

If the objective of a trend-following strategy is to distinguish between uptrend and downtrend and thereby generate excess returns relative to a benchmark price index, it may not fully achieve the goal. This is because the source of excess returns for trend-following strategies is α, and, as suggested by Figure 5, the magnitude of α is inversely related to the capture frequency. It is possible that the positive α value may have occurred incidentally due to the strategy outperforming the price index by chance.

4.2. What HMM Indicates ～How α and β differ in upward and downward trend～

What does HMM suggest, in particular, regarding the divergence in the values of α and β between the two regimes ("uptrend" and "downtrend") implied by the HMM?

(Please refer to Appendix Table for a list of the HMM parameters.)

Figure 6 presents the relationship with β in the two regimes for equity, currency, and commodity on trend-following strategies in the upper panel, and the relationship with α in the lower panel.

For β in the upper panel, it is shown that cases where the HMM outperforms tend to be plotted farther away from the 45-degree line, while cases where it underperforms tend to be plotted almost along the 45-degree line[8].

In other words, for equities, currencies, and commodities, it is suggested that the significant divergence in the value of β during uptrend phases from that of during downtrend phases, achieved by applying the HMM, is the source of excess returns.

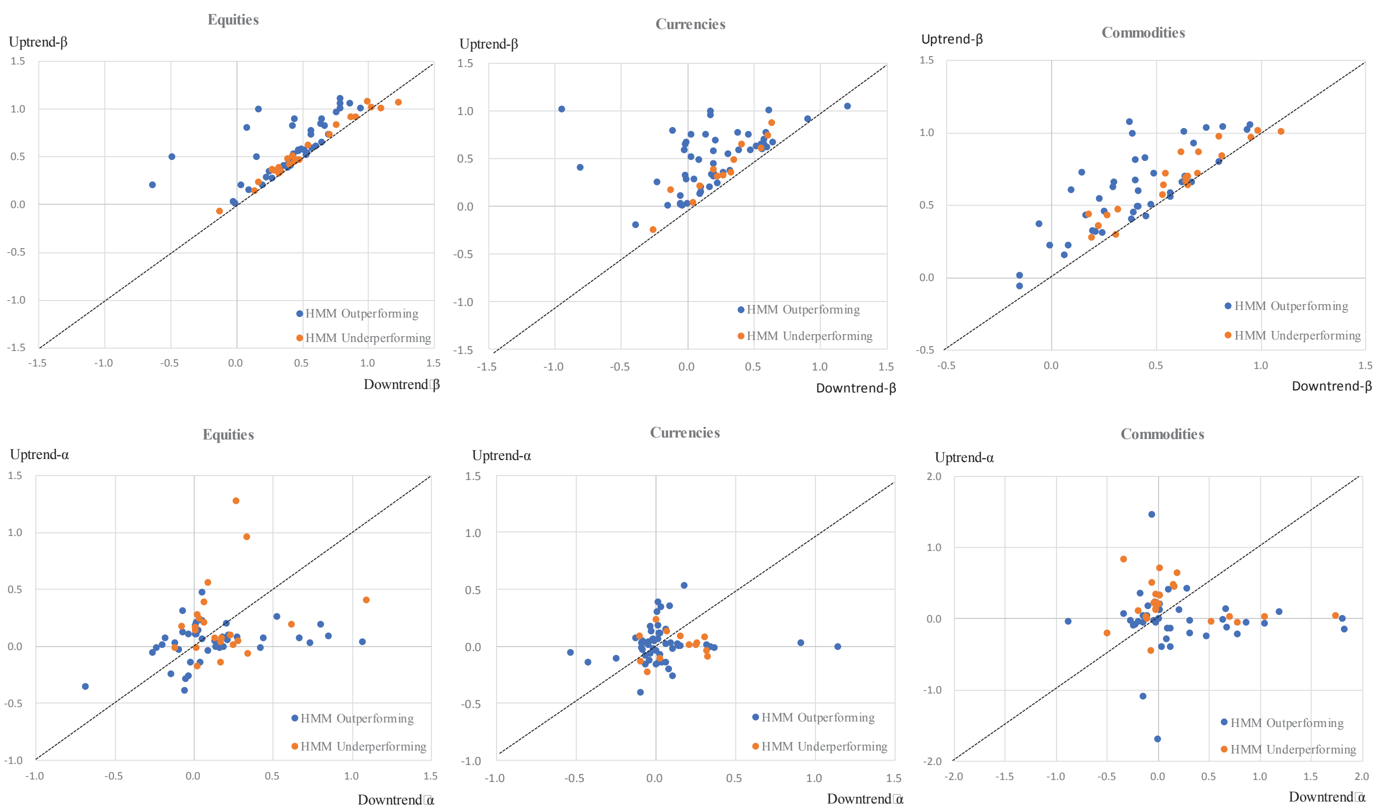
On the other hand, for α in the lower panel, no significant divergence was observed between the cases where the HMM outperformed and those where it underperformed.

This result contrasts with the findings in Section 4.1, regarding the factors driving the outperformance of trend-following strategies. In other words, it suggests that α is not the source of excess returns for the HMM.

Therefore, it can be suggested that the source of outperformance from applying the HMM to trend-following strategies lies in β. Theortically, if an uptrend is captured 100%, β will be equal to 1. In other words, the closer the value of α in the upward trend of the HMM is to 1, the more accurately in capturing the upward trend.

Returning to the upper panel of Figure 6, it can be observed that the upper bound for β when the HMM outperforms is 1. This suggests that the closer β is to 1, as a result of applying the HMM, the more likely it is that the strategy will outperform. In other words, these results indicate that combining the HMM with a trend-following strategy enhances the accuracy in capturing upward trends, suggesting the HMM being an effective tool for enhancing the core function of trend-following strategies.

Figure6 Relationship between and when HMM is applied in uptrend and downtrend



CONCLUSIONS

This paper empirically demonstrated, using data from the 2000s onward, following two key findings:

Firstly, the performance of "pure" trend-following strategies based on technical indicators is not particularly strong.

Secondlly, by applying a regime-switching model (HMM) to trend-following strategies, the probability of accurately capturing uptrends increases, thereby significantly enhancing the performance.

The focus was placed, in this paper, on empirically examining the hypothesis that applying a regime-switching model improves the performance of trend-following strategies. To ensure comprehensiveness, it included as many trend-following strategies as possible to conduct a comprehensive evaluation. However, upon closer examination of individual trend-following strategies, there were cases of performance that were comparable in the cases with and without the application of a regime-switching model (e.g., Bollinger Bands and DMI). These trend-following strategies may have a particularly high ability to extract upward trends. A detailed analysis of such individual trend-following strategies is left for future research.

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ENDNOTES

1 Refer to the literature on trend-following strategies cited in the references.e.g.Covel (2007), Covel(2011), Faith, C.(2007), and Greyserman,A.,& Kaminski, K.(2014).

2 See Michael Covel (2019) and Curtis Faith (2007) for further details.

3 For a basic understanding of the Hidden Markov Model, please refer to Hamilton (2020).

4 "Moving Average 1" classifies the price fluctuation stage of the index into six phases based on the positional relationships among short-term (13-week), medium-term (26-week) and long-term (52-week) moving averages. It adopts a strategy of initiating a "buy" position when the index is in the "stable uptrend" phase where the short-term average is above the medium-term and long-term averages. Please refer to Kojiro Instructor (2019).

"Moving Average 2" initiates a "buy" position when the momentum (the rate of increase relative to 9 weeks ago) of each moving average is positive. Please refer to Kojiro Instructor (2019).

5 For trend-following strategies other than moving averages, please refer to Nippon Technical

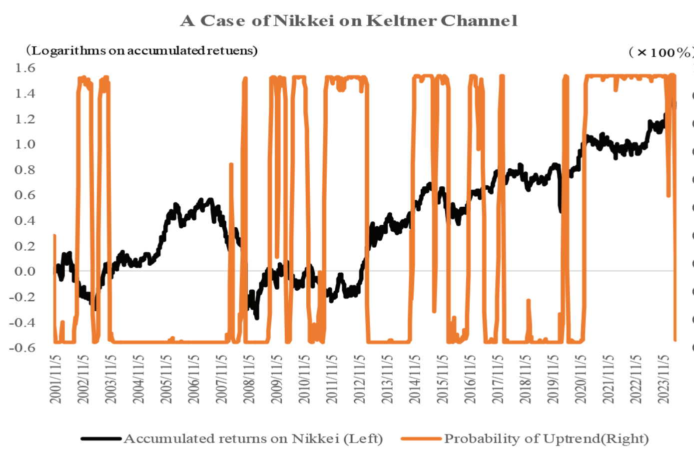
Analyst Association (2004) and Kojiro Instructor (2019).

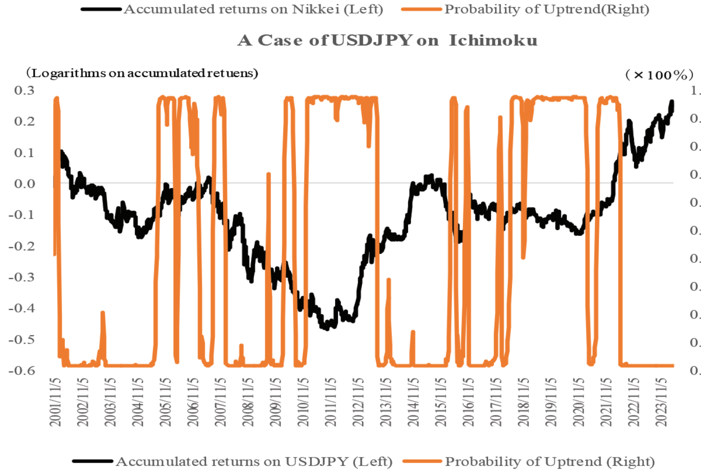
6F or a comprehensive understanding of "factor models", please refer to Ruthenberg (2009).

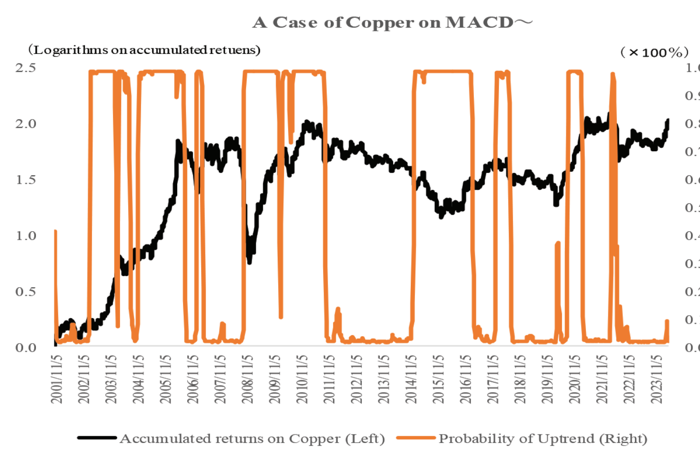
7 For examples of regime transition probabilities for the Nikkei, USD/JPY and copper, please refer to Figure A in Appendix.

8 The closer a plotted point is to the 45-degree line, the more similar the values of parameters α and α are between upward and downward trends.

APPENDIX | FigureA Examples of Regime Change Probability







APPENDIX | TableA Parameters of Factor models by Trend-following Strategies

Equities

Nikkei	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.124	0.067	0.059	0.122	0.045	0.083	0.216	-0.027	0.253	0.417	0.131
β	0.693	0.460	0.562	0.579	0.461	0.120	0.303	0.897	0.608	0.617	0.609
Dow Industrial	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.080	0.074	-0.183	0.001	-0.053	-0.009	0.164	0.079	0.117	0.124	-0.061
β	0.524	0.462	0.248	0.321	0.094	0.224	0.723	0.515	0.436	0.394	0.589
Nasdaq Composit	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.025	0.082	0.044	0.140	-0.067	0.073	0.103	-0.039	0.118	0.107	0.078
β	0.568	0.572	0.373	0.345	-0.118	0.426	0.885	0.695	0.294	0.418	0.500
EuroStoxx	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	-0.565	0.397	-0.038	0.335	-0.177	0.202	0.214	-0.162	-0.085	-0.029	-0.148
β	-0.157	0.486	0.071	0.530	-0.226	-0.593	0.293	-0.094	0.169	0.131	0.239
Nifty50	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.024	0.021	0.262	-0.163	0.159	-0.095	0.125	0.096	0.153	-0.023	-0.541
β	1.376	0.442	0.364	0.258	0.652	0.135	0.672	0.542	0.979	0.898	1.635
Shanghi Composit	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.353	0.381	0.665	0.305	0.565	0.126	0.186	0.292	0.440	0.709	0.257
β	1.333	1.402	1.328	0.548	1.577	0.721	0.853	1.281	1.682	1.783	1.124

Currencies

USDJPY	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.022	0.033	0.082	0.022	0.070	0.007	0.072	0.017	0.256	0.027	0.042
β	0.573	0.481	0.472	0.096	0.516	-0.189	0.439	0.659	0.823	0.623	0.601
AUDJPY	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.009	-0.002	0.019	0.145	-0.078	-0.349	0.014	-0.051	0.023	0.103	0.053
β	0.512	0.317	0.356	0.344	-0.087	-0.152	0.396	0.407	0.523	0.511	0.210
NZDJPY	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	-0.063	0.041	0.013	-0.017	-0.134	-0.130	0.186	0.031	0.022	0.234	0.023
β	0.382	0.320	0.198	0.349	0.101	-0.022	0.553	0.425	0.566	0.504	0.232
ZARJPY	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	-0.323	0.091	0.020	0.127	-0.015	-0.198	-0.016	0.298	0.075	-0.052	-0.056
β	1.270	0.355	-0.124	-0.235	0.138	0.108	0.611	0.569	0.184	0.680	0.473
CADJPY	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	-0.088	-0.070	0.209	0.189	0.006	-0.148	-0.039	-0.090	-0.116	0.032	-0.263
β	0.605	0.457	0.360	0.075	0.136	0.440	0.612	0.577	0.519	0.518	0.501
EURUSD	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	-0.345	0.196	0.048	0.256	-0.051	0.012	-0.039	-0.037	0.241	0.102	0.596
β	-0.901	0.246	0.140	-0.154	0.053	-0.332	0.643	0.837	-0.562	0.523	-0.317

Commodities

Coffee	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.167	0.179	0.028	-0.005	-0.104	-0.153	-0.114	-0.221	0.062	-0.360	0.194
β	2.516	0.548	0.528	0.323	0.555	0.531	0.644	0.162	1.784	0.660	2.053
Copper	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	-0.030	0.045	0.001	0.214	-0.026	-0.026	0.103	-0.361	-0.230	-0.010	-0.124
β	0.603	0.727	0.482	-0.051	0.360	0.360	0.671	0.853	1.173	0.726	0.605
Gold	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	-0.120	-0.008	-0.161	0.135	-0.080	-0.056	0.069	-0.064	0.011	-0.088	0.009
β	0.527	0.779	0.397	0.622	0.280	0.317	0.809	0.613	0.613	0.651	0.337
WTI	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.118	-0.019	0.029	0.299	-0.073	-0.320	-0.022	-0.237	-0.087	0.298	-0.056
β	0.344	0.571	0.141	0.267	-0.062	-0.754	0.457	0.206	0.411	0.574	0.204
Wheat	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.150	0.324	0.144	0.158	0.309	-0.048	-0.078	0.249	0.442	0.263	0.246
β	1.643	1.121	0.653	0.292	0.918	-0.003	0.648	0.927	1.736	1.029	1.635
Corn	Heikinashi	MA1	MA2	Bollinger	Keltner	Donchian	MACD	Three Line Break	DMI	Ichimoku	Parabolic
α	0.071	-0.139	0.121	0.102	0.097	-0.076	-0.115	-0.235	0.050	0.139	0.193
β	0.628	0.315	0.723	0.366	0.705	0.526	0.451	0.369	0.963	0.972	1.051

APPENDIX

Table B. Parameters in HMM by Trend-following Strategy

		Heikinashi		MA1		MA2		Bollinger Band		Keltner Channel		Donchian Channel		MACD		Three Line Breaks		DMI		Parabolic SAR		Ichimoku	
		Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend	Uptrend	Downtrend
Equities																							
Nikkei	α	0.312	-0.077	0.215	0.010	0.025	0.153	0.229	0.047	0.063	0.046	0.144	0.009	0.284	0.019	0.077	-0.183	-0.007	0.417	0.083	0.176	0.077	0.664
	β	0.538	0.431	0.415	0.408	0.560	0.463	0.505	0.150	0.480	0.404	0.627	0.540	0.389	0.321	0.825	0.668	0.902	0.436	0.621	0.596	0.825	0.423
Dow Industrial	α	0.049	0.127	0.167	0.006	-0.237	-0.148	-0.013	0.013	-0.010	-0.120	-0.137	0.167	0.050	0.275	0.111	0.009	0.018	0.244	-0.024	-0.100	0.060	0.212
	β	0.526	0.528	0.470	0.458	0.281	0.269	0.358	0.280	0.145	0.138	0.235	0.161	0.739	0.700	0.544	0.534	0.486	0.386	0.581	0.489	0.416	0.356
Nasdaq Composite	α	0.108	0.011	-0.006	0.137	-0.035	0.085	0.098	0.227	-0.173	0.021	0.179	-0.079	0.074	0.127	-0.139	0.035	0.245	0.031	0.037	0.167	0.071	0.174
	β	0.574	0.468	0.599	0.571	0.395	0.382	0.348	0.336	-0.066	-0.129	0.455	0.440	0.923	0.862	0.774	0.559	0.332	0.321	0.471	0.477	0.418	0.397
Eurostoxx	α	-0.350	-0.689	0.265	0.523	0.015	-0.201	0.474	0.049	-0.057	-0.267	0.097	0.216	0.199	0.203	-0.261	-0.034	-0.136	-0.025	-0.007	-0.238	0.032	-0.120
	β	0.501	-0.493	0.738	0.695	0.204	-0.641	0.810	0.079	0.039	-0.030	0.155	0.091	1.001	0.166	0.011	-0.011	0.206	0.191	0.356	0.245	0.208	0.029
Shanghai Composite	α	0.193	0.799	0.093	0.849	0.406	1.088	0.194	0.615	0.959	0.334	0.183	0.009	0.074	0.437	0.034	0.733	0.044	1.062	0.391	0.060	1.276	0.266
	β	1.011	0.783	0.974	0.753	0.926	0.902	0.369	0.266	1.072	1.023	1.010	0.936	0.738	0.561	0.898	0.644	1.059	0.855	1.026	1.021	1.087	0.989
Nity50	α	0.561	0.084	0.129	-0.074	0.216	0.060	-0.287	-0.053	-0.007	0.157	0.110	-0.036	0.085	0.270	0.142	0.026	-0.005	0.183	-0.381	-0.064	-0.059	0.337
	β	1.160	1.092	0.465	0.393	0.517	0.424	0.295	0.225	0.853	0.632	0.412	0.384	0.655	0.645	0.571	0.508	1.011	0.783	1.059	0.780	0.840	0.752
Currecies																							
USDJPY	α	0.032	-0.059	0.173	-0.034	0.358	0.088	0.116	0.018	0.348	0.035	-0.137	0.018	0.303	0.005	0.052	-0.024	0.392	0.014	0.018	0.060	0.039	-0.046
	β	0.688	0.210	0.579	0.190	0.657	-0.020	0.110	-0.053	0.521	0.026	0.204	0.164	0.757	0.022	0.771	0.377	1.002	0.167	0.597	0.557	0.673	-0.011
AUDJPY	α	0.051	-0.081	-0.023	0.106	0.060	0.015	0.234	0.001	-0.125	-0.043	-0.056	-0.533	0.093	-0.102	-0.137	0.065	0.184	0.012	-0.204	0.081	0.136	0.072
	β	0.703	0.571	0.203	0.095	0.331	0.179	0.316	0.218	0.007	-0.152	0.015	-0.045	0.491	0.344	0.587	0.472	0.311	0.189	0.280	-0.014	0.648	0.406
NZDJPY	α	-0.104	0.026	0.005	0.153	0.154	0.062	0.061	-0.015	-0.128	-0.095	-0.027	-0.082	-0.003	0.341	0.016	0.206	-0.088	0.322	-0.264	0.106	-0.041	0.318
	β	0.328	0.269	0.337	0.201	0.485	0.082	0.326	-0.022	0.045	0.037	0.378	0.320	0.961	0.170	0.386	0.194	0.880	0.634	-0.189	-0.396	0.747	0.605
ZARJPY	α	-0.142	-0.427	0.120	0.020	0.133	-0.030	0.088	0.152	-0.042	0.003	0.016	-0.049	0.033	-0.091	0.537	0.181	0.116	0.025	0.073	-0.127	-0.140	0.038
	β	1.049	1.020	0.355	0.266	0.018	-0.058	-0.247	-0.264	0.132	0.089	0.243	0.222	0.616	0.596	1.013	0.606	0.290	0.045	0.648	0.570	0.675	0.635
CADJPY	α	-0.157	0.004	-0.083	-0.064	0.085	0.305	0.032	0.260	0.048	-0.013	-0.107	-0.246	-0.064	-0.034	-0.225	-0.052	-0.162	-0.063	-0.406	-0.095	0.007	0.140
	β	0.635	0.516	0.594	0.381	0.353	0.326	0.215	0.093	0.028	-0.005	0.791	-0.115	0.769	0.586	0.610	0.548	0.756	0.137	0.450	0.189	0.550	0.303
EURUSD	α	-0.033	3.068	0.013	0.317	0.030	0.092	-0.009	0.366	-0.074	0.024	0.012	0.252	-0.023	-0.015	-0.011	-0.087	-0.006	1.141	0.031	0.909	0.019	0.133
	β	2.048	-3.442	0.592	-0.028	0.148	0.100	0.256	-0.231	0.026	-0.057	0.176	-0.128	0.752	0.453	0.915	0.901	1.017	-0.948	0.409	-0.812	0.647	0.553
Commodities																							
Coffee	α	0.000	1.803	-1.686	-0.007	0.241	-0.032	0.000	0.000	-0.044	-0.151	0.365	-0.174	-0.282	0.078	-1.081	-0.147	-0.143	1.824	0.837	-0.344	-0.200	-0.501
	β	1.089	1.067	1.076	0.370	0.508	0.474	0.431	0.161	0.678	0.400	0.320	0.207	0.827	0.446	0.813	0.397	1.035	0.738	1.087	1.051	0.672	0.638
Copper	α	-0.198	0.305	-0.243	0.467	-0.121	0.666	0.003	-0.114	-0.052	-0.022	-0.019	0.308	-0.394	0.026	0.187	-0.102	0.000	0.000	-0.022	-0.278	0.347	-0.031
	β	0.664	0.620	0.927	0.678	0.548	0.225	0.435	0.263	0.406	0.378	0.453	0.389	1.026	0.932	0.563	0.564	1.012	0.631	0.588	0.564	0.642	0.649
Gold	α	-0.050	0.858	1.466	-0.064	0.208	0.009	0.036	0.702	-0.126	0.120	-0.054	0.778	0.051	1.741	-0.065	1.043	0.129	0.014	0.142	-0.028	0.038	-0.118
	β	0.497	0.407	0.549	0.799	0.016	-0.153	0.279	0.188	0.158	0.057	0.438	0.175	0.872	0.617	0.663	0.298	0.699	0.633	0.302	0.304	0.639	0.534
WTI	α	0.454	0.156	0.118	-0.194	0.423	0.280	0.510	-0.064	-0.018	-0.047	-0.033	-0.881	0.041	-0.113	-0.394	0.113	0.068	-0.340	-0.030	-0.196	-0.214	0.772
	β	0.730	0.143	0.576	0.529	0.224	-0.010	0.472	0.313	-0.057	-0.155	0.223	0.078	0.495	0.410	0.324	0.192	0.428	0.451	0.609	0.090	0.723	0.486
Corn	α	0.134	-0.022	-0.089	-0.241	-0.006	0.627	0.327	0.016	0.220	-0.046	0.327	0.016	-0.083	-0.223	-0.441	-0.076	0.233	-0.030	0.712	0.008	-0.041	0.519
	β	0.699	0.647	0.464	0.250	0.629	0.294	0.361	0.222	0.698	0.638	0.361	0.222	0.602	0.414	0.723	0.541	0.975	0.799	0.840	0.809	0.868	0.701
Wheat	α	0.031	1.040	0.483	0.145	0.212	0.005	0.131	0.203	0.461	0.157	-0.138	0.086	0.041	-0.147	0.140	0.663	0.642	0.183	0.098	1.183	0.408	0.096
	β	1.015	0.982	1.013	1.094	0.721	0.693	0.313	0.240	0.969	0.951	0.371	-0.063	0.660	0.669	0.995	0.386	1.073	1.056	1.040	0.816	1.054	0.946

AI-Based Dynamic Asset Allocation For Uncertain Markets

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Abstract

In the realm of modern portfolio management, the pursuit of optimal strategies that deliver consistent profits while mitigating the adverse impacts of market volatility and drawdowns is of paramount importance. Conventional static allocation portfolios and the widely employed buy-and-hold strategy have demonstrated vulnerability to significant drawdowns, particularly in turbulent market conditions. Therefore, this paper advocates a paradigm shift towards a more resilient approach, exemplified by a total return framework that harnesses the potential of a multi-asset strategy. This study explores the development and analysis of an innovative multi-asset dynamic allocation model, aiming to strike a balance between preserving profits over time and consistent risk-adjusted performance by incorporating recent scientific developments relevant to financial market analysis. The proposed model offers a promising avenue for effective portfolio management in today's dynamic and volatile financial landscape.

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INTRODUCTION

1.1 Uncertain times require dynamic allocation

This paper outlines a sophisticated quantitative dynamic asset allocation strategy, focusing on U.S. equity sectors and incorporating "risk-off" assets to build a versatile and adaptable portfolio. The strategy's essence lies in its ability to dynamically adjust to economic and market cycles, emphasizing resilience through diversification and dynamism to withstand market volatilities, including potential crashes outlined in Table 1.

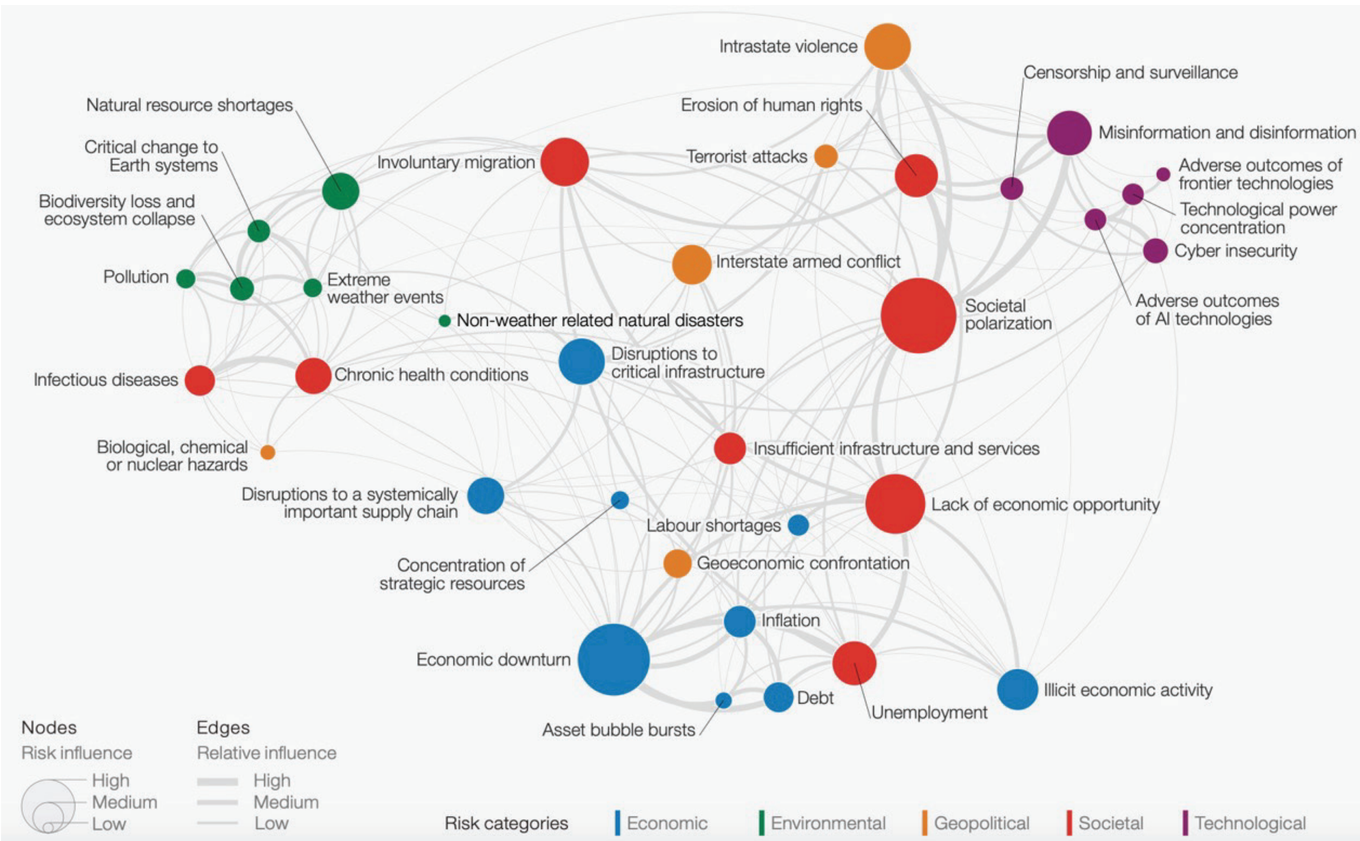
Table 1. Global risks ranked by severity over the next 2 years. Source: World Economic Forum Global Risks Perception Survey 2023-2024

1	Misinformation and disinformation
2	Extreme weather events
3	Societal polarization
4	Cyber insecurity
5	Interstate armed conflict
6	Lack of economic opportunity
7	Inflation
8	Involuntary migration
9	Economic downturn
10	Pollution

Legend: Risk Categories
Environmental
Societal
Technological
Geopolitical
Economic

The approach leverages spectral analysis of the S&P 500 covariance matrix to assess market conditions, using dominant modes as indicators to recalibrate the portfolio under irregular situations. Additionally, it incorporates robust market sentiment analysis and higher-order correlation assessments through advanced mathematical tools like the O-information framework, moving beyond traditional methods to identify market trends. Implementing explainable AI, the strategy utilizes time series data to align the portfolio with current sector trends, highlighting its reliability, scalability, and adaptability. This approach not only seeks to enhance portfolio management but also to navigate the complexities of modern financial landscapes, as depicted in Figure 1, aiming for a sophisticated management system that can effectively respond to changing market dynamics.

Figure 1. Global risks landscape: an interconnections map. Source: World Economic Forum Global Risks Perception Survey 2023-2024



MATERIALS AND METHODS

This section delves into the data sources and primary technical tools utilized in the strategy. These tools represent some of the latest advancements in the scientific field relevant to financial market analysis. For a clearer understanding of how the strategy functions, this part is divided into subsections.

2.1 Data sources and software utilized

This study utilizes data solely from the Bloomberg database, encompassing a wide array of financial instruments and metrics, to assess a trading strategy over the period January 2007 to November 2023. It involves gathering time series and datasets from past market periods, which vary in range and are utilized in different stages of the research. The paper will elaborate on the specific applications and importance of these diverse datasets, highlighting their key components:

- **Sectoral ETFs time series:** Daily data on U.S. sectoral ETFs from January 2003 to November 2023, progressively as they became available in the market, as detailed in Table 2.

Table 2. US Sectoral ETFs

Sector ETF name	Ticker
SPDR Materials	XLB
SPDR Communication Services	XLC
SPDR Energy	XLE
SPDR Financial	XLF
SPDR Industrial	XLI
SPDR Technology	XLK
SPDR Consumer Staples	XLP
SPDR Real Estate	XLRE
SPDR Utilities	XLU
SPDR Healthcare	XLV
SPDR Consumer Discretionary	XLY

- **"Risk-Off" basket time series**: Daily data on ETFs representing safe-haven assets (such as currencies, bonds, gold...) as listed in Table 3, progressively as they became available in the market from January 2003 to November 2023.
- **Volatility and sentiment indicators time series:** Daily data from January 2008 to November 2023 on market volatility and sentiment, including the S&P 500 put/call ratio, AAII Bull-Bear spread, historical VIX, and 3-month VIX futures, crucial for computing the VIX Ratio.

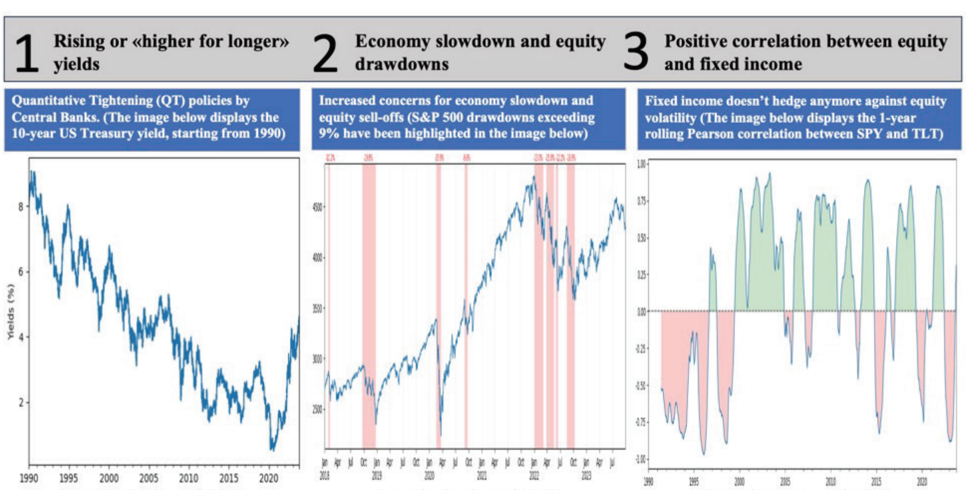
Table 3. "Risk-Off" ETFs basket

ETF name – Asset Class	Ticker
Invesco CurrencyShares Swiss Franc (CHF)	FXF
Invesco CurrencyShares Japanese Yen (JPY)	FXY
SPDR Gold	GLD
iShares 7-10 Years Treasury Bond	IEF
ProShares Short S&P500	SH
iShares 1-3 Years Treasury Bond	SHY
iShares 20+ Years Treasury Bond	TLT

- **Equity Sectors and Risk-off baskets proxies:** Time series data for SPY (SPDR S&P 500 ETF) and TLT (iShares 20+ Year Treasury Bond ETF) from October 2003 to November 2023 used as proxies for U.S. equity sectors and safe havens in Sharpe Ratio optimization calculations.
- **S&P 500 constituents time series:** Comprehensive data collection on S&P 500 stocks from January 2003 to November 2023, with annual refreshes to reflect the index's evolving composition. This methodology captures the dynamic nature of the S&P 500, enhancing the research's accuracy and market relevance.

The research utilized Python for data processing and analysis due to its versatility, extensive scientific libraries, and performance superiority over other financial programming languages. Tools such as scipy, pandas, tensorflow, pytorch, and SHAP were employed to facilitate calculations, modeling, and statistical evaluations. This methodology, including Python and its libraries, formed a solid foundation for examining market dynamics and challenges, as presented in Figure 2, from a computational perspective.

Figure 2. Biggest challenges impacting long-only investors today (as of Q4 2023)



2.2 Markets modes analysis

The study also delves into market modes analysis, traditionally focusing on stock markets and the examination of correlations between equity time series, such as with Granger causality. This method is useful for identifying redundancies in time series data, offering insights into how individual stocks relate to broader market movements. However, it lacks depth in predicting market direction

The application of Random Matrix Theory (RMT), initially explored by Laloux (1999, 2000) in his studies, is highlighted for its effectiveness in addressing these limitations. RMT, a branch of probability theory that studies the properties of large random matrices, can discern global correlations and provide insights into the market's state through the analysis of the correlation matrix of time series like the S&P 500. Notably, research by Bouchaud and Potters (2015), Ludescher (2011), and Heckens (2020) showcases RMT's capability to identify collective market states and detect conditions that may precede market downturns, offering valuable forecasts for portfolio management to mitigate potential losses.

This analysis centers on developing a market matrix, $\boldsymbol{M(t)}$, that accounts for market dynamics over time, with time broken down into quarters, each consisting of 63 trading days. For any given quarter, $\boldsymbol{q_\alpha}$, defined by a set $\{\alpha T, \alpha T+1, \dots, (\alpha+1)T-1\}$ (where $\boldsymbol{\alpha}$ marks the quarter number from the start), we examine the logarithmic returns of stock $\boldsymbol{i}$ after a delay $\boldsymbol{\Delta t}$, represented as

$$G_i(t) = \log\left(\frac{P_i(t+\Delta t)}{P_i(t)}\right),$$

where $\boldsymbol{P_i(t)}$ is the adjusted closing price on day $\boldsymbol{t}$. The focus is on computing time-averaged mean $\mu_i(q_\alpha)$ and standard deviation $\sigma_i(q_\alpha)$ for each quarter, leading to the normalization and centering of log-returns within each quarter as

$$M_i(t)\big|_{q_\alpha} = \frac{G_i(t) - \mu_i(q_\alpha)}{\sigma_i(q_\alpha)}, \; t \in q_\alpha.$$

This preparation allows for constructing a Pearson correlation matrix

$$C(q_\alpha) = \frac{1}{T} M(q_\alpha) M(q_\alpha)^t$$

for each quarter.

The study employs spectral clustering on these correlation matrices to identify clusters of matrices that represent similar market conditions, such as crisis or bubble states, within historical time series. This clustering is crucial for real-time analysis, enabling the categorization of current market states and guiding decision-making. A significant metric in this analysis is the largest eigenvalue λ_1 of $C(q_\alpha)$, which offers deeper insights beyond simple clustering and is instrumental in strategy implementation. This methodology builds upon the foundational work in correlation and covariance matrix analysis, dating back to Wishart (1928) and further developed by Silverstein and Bai (1973), showcasing its application in distinguishing different market phases.

2.3 Time series correlations through O-information

The section discusses the limitations of Random Matrix Theory (RMT) in analyzing correlations between equities and safe heaven assets, noting its inadequacy due to the negligible influence of individual elements within large matrices, such as a 501x501 matrix when comparing the S&P 500 to 10-year U.S. treasury bonds.

To address these challenges, the paper presents the O-information method, developed by Rosas et al. (2019), as an extension of Shannon information entropy. This method is a promising tool for uncovering the dynamics of higher-order dependencies among multiple interacting variables, marked by synergy (where the combined effects surpass the contributions of individual variables) and redundancy (where the overall effect is less than the sum of its individual parts).

O-information aims to determine whether market information is merely the sum of individual components or if interactions among parts create a dynamic that surpasses individual contributions. It uses a framework where the total correlation ($\mathcal{T}$) and dual information ($\mathcal{D}$) metrics are defined using Shannon entropy. $\mathcal{T}$ measures the unique information of a system beyond its components, while $\mathcal{D}$ quantifies the information gap between understanding the whole system and the incremental gain from adding one variable at a time. O-information ($\mathcal{O}$) is then calculated as the difference between $\mathcal{T}$ and $\mathcal{D}$, indicating a predominance of synergy when $\mathcal{O}$ <0 and redundancy when $\mathcal{O}$ >0, providing a nuanced view of market dynamics beyond pairwise comparisons.

2.4 Machine Learning models and explainable AI

The strategy aims to manage portfolios by leveraging insights from the current market conditions and the interconnections between stocks and other assets, employing cutting-edge machine learning technologies instead of traditional deterministic algorithms. This method enhances the strategy's resilience, as machine learning's adaptable nature allows it to adjust to unforeseen scenarios not covered in its training data. Adaptability is crucial, considering each financial bubble and crisis has distinct features that require specific strategies for effective capital management. However, a limitation of machine learning is its "black box" nature, where the rationale behind its outcomes can be obscure. To mitigate this, Explainable AI has been introduced to make the decision-making process clearer and more understandable.

2.5 Long Short-Term Memory (LSTM) models

The introduction of Long Short-Term Memory (LSTM) models by Hochreiter and Schmidhuber (1997) revolutionized recurrent neural networks (RNNs) by addressing the challenges of exploding and vanishing gradients, thus enabling the learning of long-term dependencies. This advancement is key for processing sequences with significant time gaps, enhancing models' ability to handle complex sequences like those in financial markets.

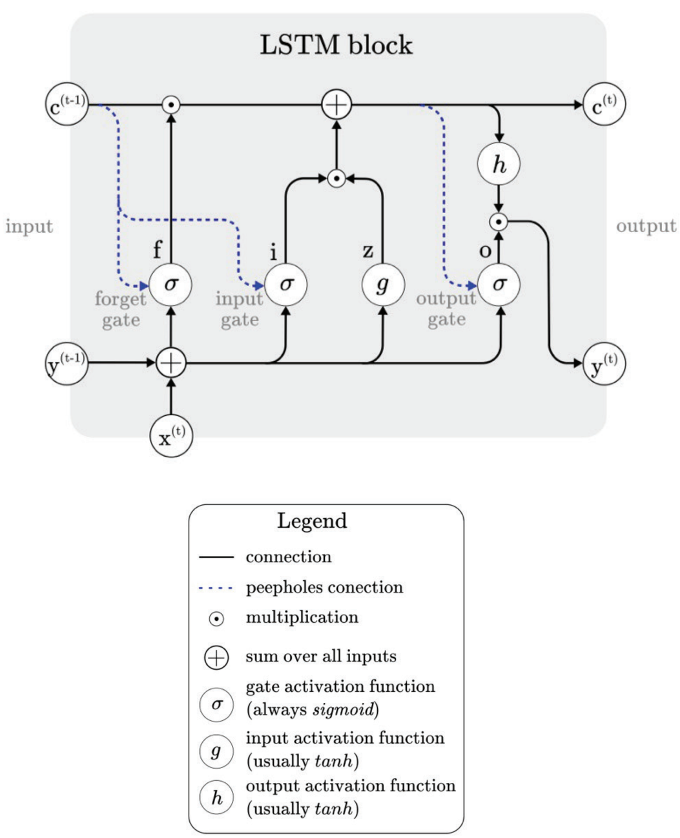
LSTMs are structured with a cell and three gates: input, output, and forget—the latter introduced to refine memory updating capabilities. This design allows LSTMs to effectively manage data flow and information preservation over time:

1. The cell state update equation, $c(t) = f(t)\cdot c(t-1) + i(t)\cdot \tilde{c}(t)$, shows how the memory evolves, influenced by the forget gate's activation \(f(t)\), the input gate's activation *i(t)*, and the candidate value for addition $\tilde{c}(t)$.

2. The forget gate uses $f(t) = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$ to decide what information to discard, employing the sigmoid function (σ), weights (W_f), bias (b_f) the previous output $[h_{(t-1)}, x_t]$, and the current input x_t.
3. The input gate and candidate value ($\tilde{c}(t)$) work together to update the cell state with new information, using the equations $i(t) = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ and $\tilde{c}(t) = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$.
4. The output gate's function $o(t) = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$ and the resulting hidden state $h_t = o(t) \cdot \tanh(c(t))$ demonstrate how output is determined.

The "vanilla" LSTM model, see Figure 3, with its specialized memory blocks and gating mechanisms, excels at retaining information for long periods, crucial for regulating information flow. Its application in financial forecasting models has proven significantly effective for analyzing market trends, capturing long-term dependencies, and enhancing prediction accuracy. This success in financial analysis underscores LSTMs' vital role in advancing forecasting techniques, improving investment strategies, and portfolio management.

Figure 3. Architecture of a typical vanilla LSTM block.



2.6 Explainable AI

Explainable AI enables understanding complex machine learning models by tracing their strategies to interpretable parameters, using tools like SHAP. SHAP employs Shapley values to evaluate the significance of individual features within a model, interpreting the model's optimization as a cooperative game where features are players in a coalition. With $[\boldsymbol{n}]$ representing the set of features and $\mathcal{P}([\boldsymbol{n}])$ their possible coalitions, a strategy s assesses the coalition's total effectiveness, $\mathcal{C} \in \mathcal{P}([\boldsymbol{n}])$. The formula for the Shapley value of feature $\boldsymbol{i}$ ($\boldsymbol{i} \in [\boldsymbol{n}]$) is:

$$\varsigma_i(v) = \sum_{\mathcal{C}\in\mathcal{P}([n])\setminus i} \frac{|\mathcal{C}|!\,(n-|\mathcal{C}|-1)!}{n!}\left(v(\mathcal{C}\cup i) - v(\mathcal{C})\right)$$

This equation calculates the marginal contribution of feature i to the coalition's overall success, representing its value in the model's output.

RESULTS

3.1 Investment philosophy

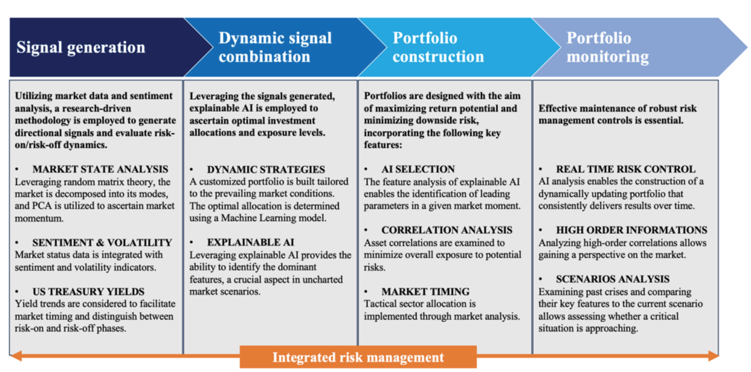
The investment philosophy presented focuses on innovative solutions to address contemporary challenges, leveraging recent advancements in mathematical and statistical tools to develop superior investment strategies. This philosophy aims for long-term capital growth, emphasizing optimizing returns while maintaining a high tolerance for risk. An active risk management approach is integral, aiming to minimize downside risk.

The strategy is implemented through a series of systematic steps, starting with an analysis of the stock market using random matrix theory to assess the S&P 500's logarithmic returns. This provides insights into market conditions such as crises and trends, informing portfolio composition decisions. The strategy also incorporates market momentum, sentiment, and U.S. Treasury yield trends through an interpretable machine learning model, optimizing portfolio composition by integrating various signals. This process allows for strategy adaptation in response to market changes, including extreme scenarios not reflected in historical data.

Furthermore, the strategy evaluates asset redundancy to construct robust portfolios, using information theory (specifically O-information) to analyze asset time series' synergy and redundancy. This method enhances portfolio resilience against market volatilities.

Overall, the philosophy summarized in Figure 4 aims to achieve superior risk-adjusted portfolio performance, capitalizing on cutting-edge analytical tools and methodologies to navigate dynamic market conditions effectively.

Figure 4. The AI-based dynamic asset allocation investment process



3.2 Asset Allocation Optimization through Sharpe Ratio Forecasting

The strategy focuses on forecasting market trends for the next 42 trading days, aiming to optimize the portfolio Sharpe ratio to achieve the best possible balance between expected forecasted risk and minimizing the portfolio's average rebalancing rate. The Sharpe Ratio, introduced by Nobel Laureate William F. Sharpe, is a key metric for assessing risk-adjusted returns. It measures the extra return over the risk-free rate per unit of risk, calculated as

$$\text{"Sharpe Ratio"(SR)} = \frac{R_p - R_f}{\sigma_p},$$

where R_p is the average return on investment, R_f is the risk-free return rate, and σ_p, is the standard deviation of the investment's returns

To optimize the Sharpe Ratio, the objective is to maximize the formula $max \frac{R_p - R_f}{\sigma_p}$, subject to constraints like the total asset weights in the portfolio being equal to 1, possible restrictions on individual asset weights, and non-negativity constraints if short selling is disallowed. A Long Short-Term Memory (LSTM) forecasting model is used to predict the optimal allocation between U.S. sector-specific ETFs and safe-haven assets, specifically focusing on forecasting the optimal weights between SPY and TLT for the portfolio 42 trading days in advance. This is aimed at determining the risk-adjusted average excess returns of the stock market compared to "risk-off" assets.

3.3 Walk-forward Optimization

The dataset was divided into overlapping segments, with each segment containing 1,000 data points, split into 750 for training and 250 for testing. This approach is known as walk-forward training, recognized for its practical benefits in modeling, including:

- **Realism:** It uses unseen data for testing, mimicking real-world conditions and ensuring strategies are viable for future data.
- **Reduced Overfitting:** Regular testing on new datasets helps prevent overfitting, making models more reliable on unseen data.
- **Robustness:** Success across multiple testing cycles indicates stability and adaptability to changing conditions.
- **Market Adaptation:** Models can adjust to new trends and market dynamics through periodic re-optimization.
- **Performance Validation:** Offers a framework for confirming a model's reliability over time.
- **Parameter Optimization:** Permits the dynamic update of parameters using recent data for better performance.
- **Forward-looking:** Assesses a model's performance on future data, which is essential for making accurate predictions.

While walk-forward optimization enhances predictive accuracy and adaptability, it faces challenges such as computational demands and the complexity of managing numerous training and testing cycles. Nonetheless, for areas requiring high predictive precision over time, like financial trading, it provides a robust framework for model validation and optimization.

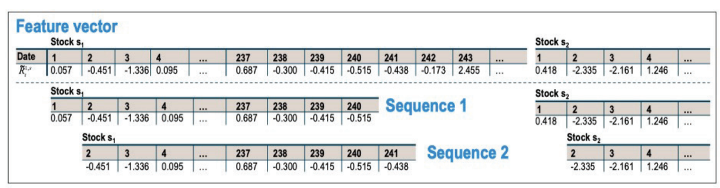
3.4 Features and Targets of the LSTM model

In the context of machine learning, features are input variables from which a model learns to predict outcomes, while targets are the outcomes the model aims to predict. An LSTM model was employed, using the following features:

- **the largest eigenvalue of the market correlation matrix:** A time series, represented as $\lambda_{max}(t)$, was developed. This series calculates the largest eigenvalue, λ_{max}, of the market correlation matrix for each day t, using data from the previous 42 days. The correlation matrix is based on stocks that remained constant in the dataset, amounting to around 170 companies. These stocks, notable for their high market capitalization, provide a solid representation of overall market trends
- **Time series of volatility and sentiment metrics.**
- **Sharpe Optimal Weights:** The study incorporated a time series that identified the optimal weight for the portion of the portfolio considered "risky," aiming to maximize the Sharpe ratio over the previous 63 trading days.

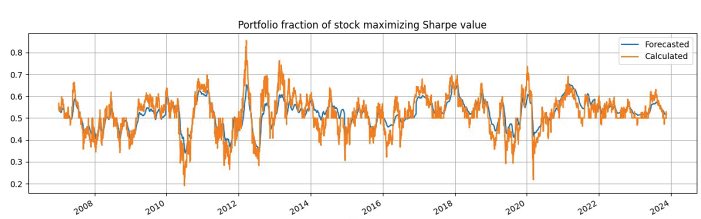
The model uses 240 consecutive data points from these features to predict the optimal portfolio weight for the next 42 days. To avoid look-ahead bias, the training data ends 42 days before the testing set starts. The training set begins in January 2007, after a 1,000 trading days window starting on January 9th, 2004. The testing windows are arranged such that each starts immediately after the previous one ends, as shown in the example in Figure 5.

Figure 5. Construction of input sequences for LSTM networks



The model's predictive ability in optimizing the Sharpe ratio for the forthcoming two months is demonstrated through Figure 6 that compares the actual risk-adjusted return (orange line) and the LSTM forecasted optimal weight (blue line) from 2007 to 2024. The close correlation between the forecasted and actual values, especially during volatile market periods, indicates a robust model capable of dynamically adjusting portfolio allocation to maximize the Sharpe ratio.

Figure 6.Predicting the Optimal Equity Share in the Portfolio to Maximize Next Month's Sharpe Ratio Value.



Post-2008 financial crisis, the model shows adaptability by adopting a conservative approach during market recovery and a more aggressive stance as stability returns. This adaptability suggests that the model can facilitate stable growth and improved risk-adjusted returns over time by proactively managing risk and optimizing performance through strategic rebalancing in response to market changes.

3.5 Asset selection and rebalancing frequency

After obtaining the optimal weights for allocating capital among risky and safe heaven assets, two critical aspects of the strategy emerge: asset selection and rebalancing frequency.

Asset Selection: This phase entails the creation of two LSTM (Long Short-Term Memory) networks designed to forecast the momentum of individual assets within a designated selection. The timeframe spans from January 2007 to November 2023, divided into trading intervals of 1,000 days each, with a division of 750 days for training purposes and 250 days for testing. The input for these models consists of time-series data related to standardized, mean-adjusted daily returns of assets, as specified in Table 2 for U.S. Sector ETFs and in Table 3 for assets deemed as safe havens during periods of "risk-off" cycles. The primary objective of the model is binary classification, aimed at evaluating a series of features over 240 trading days within each 1,000-day period to predict if a specific asset will outperform the median return in the following trading month. The binary classification outcome of the LSTM is represented through a vector whose entries correspond to the number of assets n_w available at the beginning of the training interval. Each vector entry n_w indicates the probability that the associated asset will exceed the median return over the subsequent 21 trading days.

For portfolio construction, at every rebalancing juncture, the upper half $\left\lceil \frac{n_w}{2} \right\rceil$, rounded up, of the assets from each category considered at the start of the 1,000-day trading period is selected. Particularly, the selection favors the upper half of the assets, allocating portfolio weights based on their predicted chances of surpassing the median return. This approach favors assets anticipated to yield superior performance while simultaneously maintaining portfolio diversification to mitigate significant market swings. It's crucial to acknowledge that the financial instruments involved do not remain consistently available throughout the 2007 to 2023 timeframe. For instance, in the segment focusing on "risk-off" ETFs, the initial 1,000-day trading phase begins with merely three tradable instruments: IEF, SHY, and TLT. This method requires the selection of a minimum of $\left\lceil \frac{3}{2} \right\rceil$=2 assets from this group at any given time during the specific trading interval.

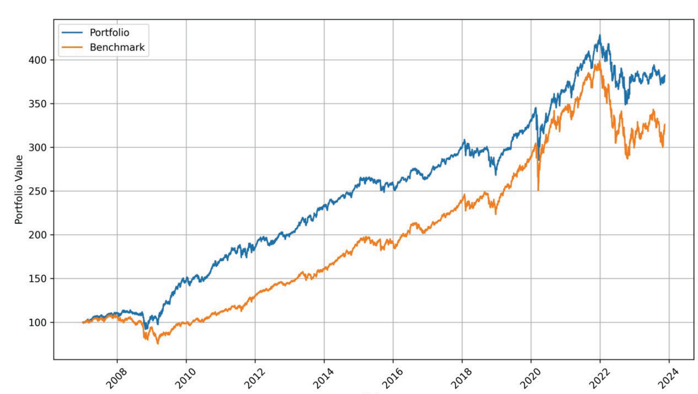
Rebalancing Frequency and Trigger Events: Maintaining an optimally balanced portfolio that aligns with specific Sharpe Ratio criteria necessitates establishing clear rebalancing guidelines. This process involves updating the portfolio's asset allocation by selecting assets forecasted to outperform the median return within their categories and assigning weights based on their anticipated performance. The strategy mandates bi-monthly adjustments to the portfolio. Post-rebalance, strategy updates are withheld unless forecasted allocations, optimized for the Sharpe Ratio, significantly diverge from current holdings. A mandatory rebalance is initiated upon detecting a variation exceeding a 27% threshold, identified as optimal for meeting the objectives.

This threshold is designed to minimize rebalancing frequency—considering transaction costs at 10 basis points per trade—while remaining responsive to significant market changes within each two-month cycle. Opting for a lower threshold might trigger excessive responses to minor market shifts, elevating transaction costs, whereas a higher threshold risks overlooking necessary adjustments during major market downturns. Critical analysis of these parameters for potential biases is imperative, focusing on their effectiveness across the entire trading dataset to enhance strategy performance uniformly, rather than achieving anomalously high returns in a restricted market period. The strategy's average trajectory illustrations confirm that this meta-parameter effectively fine-tunes the approach across the dataset, avoiding optimization that benefits only specific periods.

3.6 Balancing Risk and Reward: Achieving better risk-adjusted returns

Figure 7 shows a comparison between the dynamic investment strategy (in blue) and a benchmark (in orange), using a lazy portfolio mix of 60% SPY and 40% TLT, from January 2007 to November 2023. The dynamic strategy outperforms the benchmark with a +282% return versus +226%, boasting an annualized return of 8.2% against 7.1%. In summary, the portfolio demonstrates resilience during downturns, quick recovery, and effective risk management, yielding a more reliable return profile amidst market fluctuations.

Figure 7. Performance comparison between the Strategy (in blue) and the Benchmark (in orange)



Key insights include:

- **Greater Capital Appreciation:** The strategy's significant and consistent growth, achieving higher long-term returns.
- **Resilience During Market Downturns:** Indicates better loss containment compared to the benchmark.
- **Quicker Recovery Post-Downturns:** Highlights faster rebound capabilities, reducing opportunity costs.
- **Risk Management:** Shows controlled fluctuations for a steadier performance.

Table 4. Analysis of monthly and annual performance for the Strategy juxtaposed with its benchmark

	January	February	March	April	May	June	July	August	September	October	November	December	Total	Benchmark	Alpha
2007	0.95%	1.15%	0.65%	3.05%	1.28%	-0.92%	-1.11%	1.58%	1.95%	1.64%	-0.06%	0.25%	10.84%	6.93%	3.91%
2008	-0.74%	2.40%	-1.14%	-0.34%	1.00%	-1.08%	-0.64%	-0.60%	-1.05%	-11.43%	5.92%	5.08%	-3.60%	-12.30%	8.69%
2009	-0.49%	-4.68%	6.03%	6.69%	7.57%	-0.27%	6.98%	2.39%	3.89%	0.43%	5.68%	-1.39%	37.10%	4.75%	32.35%
2010	-1.85%	2.01%	3.01%	1.65%	-3.58%	-0.02%	2.32%	2.30%	4.35%	2.80%	-0.38%	4.13%	17.72%	14.04%	3.68%
2011	-0.31%	3.04%	0.64%	3.95%	-0.05%	-0.73%	1.10%	-0.95%	-4.82%	7.15%	0.23%	-1.88%	7.10%	15.97%	-8.87%
2012	4.58%	0.99%	1.15%	-0.29%	-3.83%	1.85%	0.69%	2.40%	1.35%	-1.09%	0.59%	-0.44%	8.01%	10.79%	-2.78%
2013	1.63%	1.07%	2.78%	2.10%	0.33%	-0.75%	3.26%	-2.18%	2.83%	3.10%	1.03%	1.24%	17.56%	12.03%	5.53%
2014	-1.44%	3.50%	-0.40%	0.01%	1.27%	1.15%	-0.68%	2.81%	-1.13%	1.71%	2.56%	-0.10%	9.49%	18.39%	-8.90%
2015	2.38%	0.84%	-0.67%	0.04%	0.24%	-1.78%	1.50%	-3.57%	-0.81%	3.12%	-0.78%	0.28%	0.61%	-0.12%	0.74%
2016	-1.13%	1.66%	1.96%	-0.64%	0.06%	2.57%	2.22%	-0.69%	-0.28%	-1.47%	-1.98%	0.39%	2.58%	7.62%	-5.04%
2017	1.88%	2.67%	0.00%	1.11%	1.56%	-0.43%	1.38%	1.04%	-0.12%	0.66%	1.68%	0.99%	13.10%	16.14%	-3.04%
2018	2.49%	-2.11%	-2.21%	-1.20%	1.47%	-0.97%	1.68%	0.68%	-0.72%	-4.99%	1.81%	-3.32%	-7.43%	-3.04%	-4.39%
2019	4.03%	1.27%	1.80%	0.87%	-0.57%	4.43%	0.58%	1.41%	0.70%	0.53%	1.07%	1.91%	19.47%	24.24%	-4.77%
2020	1.25%	-4.41%	-4.44%	5.58%	1.91%	1.55%	4.35%	2.25%	-1.46%	-1.17%	4.68%	1.04%	11.06%	20.72%	-9.65%
2021	0.14%	-1.65%	2.35%	3.97%	1.65%	0.28%	2.67%	1.15%	-4.29%	4.97%	0.30%	4.31%	16.61%	14.43%	2.19%
2022	-4.21%	-0.59%	1.70%	-6.76%	0.97%	-5.26%	3.61%	-3.06%	-5.93%	4.04%	5.15%	-1.46%	-12.02%	-23.86%	11.84%
2023	2.23%	-2.69%	1.94%	0.45%	-2.91%	3.06%	2.16%	-1.75%	-2.29%	-0.74%	2.18%		1.40%	7.89%	-6.49%

Continuing with the analysis, Table 4 provides a detailed monthly and annual performance comparison, showing the strategy's superior risk-adjusted returns through different cycles. Notable findings include:

- **Reliable Performance Across Conditions:** Demonstrated by consistent positive alpha, indicating effective asset selection and timing with a Sharpe ratio of 0.75 (versus 0.59 for the benchmark).
- **Robust Performance in Market Dips:** Reflects the strategy's capacity to minimize declines, crucial for capital preservation.
- **Smooth Return Profile:** Minor annual return fluctuations suggest a stable investment path.
- **Efficient Excess Return Generation:** The consistent positive alpha over years highlights effective risk management and return generation.

Observing the heatmap in Figure 8 visualizes the strategy's monthly returns, indicating mostly green for strong returns and occasional red for lower ones. This pattern indicates sustained positive performance and resilience, with quick recoveries from setbacks, aligned with goals of capital preservation and growth.

Figure 8. The heatmap illustrates the monthly returns generated by the investment strategy.

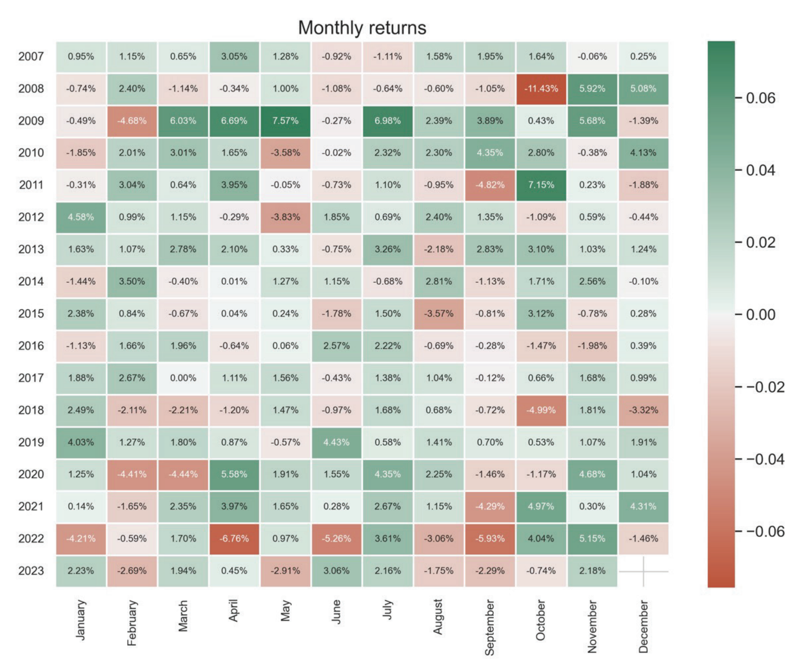
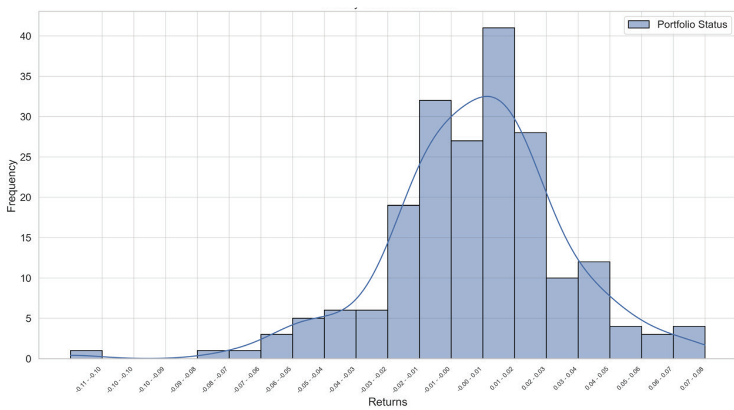


Figure 9's histogram and distribution curve reveal a bell-shaped return distribution with a modest positive skew (skewness of 0.012 versus 0.45 for the benchmark), suggesting a strategy that leans towards generating stable gains without extreme losses, evidenced by a kurtosis value of -1.056. This aligns with a disciplined, risk-managed approach focusing on consistent performance over high-risk ventures.

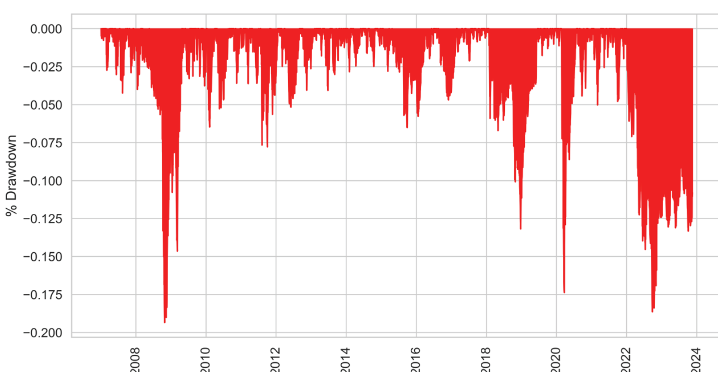
Figure 9. Distribution of monthly returns for the investment strategy.



3.7 Protecting Investments Against Market Stress

The chart in Figure 10 illustrates the daily drawdown profile for an investment strategy from January 2007 to November 2023, focusing on the significant dips in portfolio value. Drawdowns, measured in percentage, highlight the strategy's negative deviations from its peak performance, with notable drops occurring on October 28, 2008 (19.3% decline) and September 26, 2022 (18.6% decline).

Figure 10. Drawdown Profile of the Strategy (January 2007 - November 2023)



These drawdowns are essential for understanding the strategy's resilience and risk management, particularly its ability to recover from such downturns. Despite the severe declines, the strategy's effective navigation through market challenges is evident, with limited prolonged downturns—2022 being an exception—indicating its adept management and market resilience. The intervals between drawdowns potentially signal periods of positive performance and capital growth, contributing to the strategy's overall resilience and ability to preserve and grow capital despite market volatilities.

Table 5 delves into the strategy's performance during the market's worst months from 2007 to November 2023, comparing it to a benchmark. It highlights the strategy's consistent outperformance during these periods, as shown by positive alpha values, demonstrating its capacity to exploit unfavorable conditions to the benchmark's detriment.

Table 5. Monthly performance of the strategy vis-`a-vis the benchmark during challenging market intervals.

Dates	Portfolio	Benchmark	Alpha
2008-09-30	-1.05%	-5.06%	4.01%
2008-10-31	-11.43%	-10.76%	-0.68%
2009-01-31	-0.49%	-10.24%	9.76%
2009-02-28	-4.68%	-7.18%	2.50%
2018-10-31	-4.99%	-5.33%	0.34%
2022-01-31	-4.21%	-4.78%	0.56%
2022-04-30	-6.76%	-9.10%	2.34%
2022-06-30	-5.26%	-5.47%	0.22%
2022-09-30	-5.93%	-8.85%	2.92%
2022-12-31	-1.46%	-4.56%	3.10%
2023-09-30	-2.29%	-5.99%	3.70%

Overall, the strategy showcases a balanced and effective approach to market navigation, underlined by its consistent outperformance, resilience, and dynamic response to market fluctuations over the analyzed period. This approach not only mitigates losses during market downturns but also accentuates the strategy's adaptability and long-term value preservation.

3.8 Evaluating Strategy Stability

Figure 11 presents three plots, detailing different rolling metrics from January 2007 to November 2023:

- **Top Plot (Rolling 1-Year Annualized Standard Deviation of Returns):** Shows strategy volatility with peaks (high uncertainty) and valleys (stability), indicating a decreasing volatility trend, suggesting improved strategy performance and risk management. The average volatility is 9.33%.
- **Middle Plot (Rolling 1-Year Correlation to the Benchmark):** Displays the correlation between the strategy and benchmark returns, mostly ranging between 0.8 and 0.9, highlighting a strong, positive connection.
- **Bottom Plot (Rolling 1-Year Beta to the Benchmark):** Examines portfolio volatility against a benchmark, showing a beta generally below 1, implying less volatility than the benchmark, except during 2012-2013 when it slightly exceeded 1 (peak of 1.1). Despite lower volatility, the strategy

yields higher annualized returns than the benchmark, indicating it's a viable option for risk-averse investors seeking a balance between risk and performance.

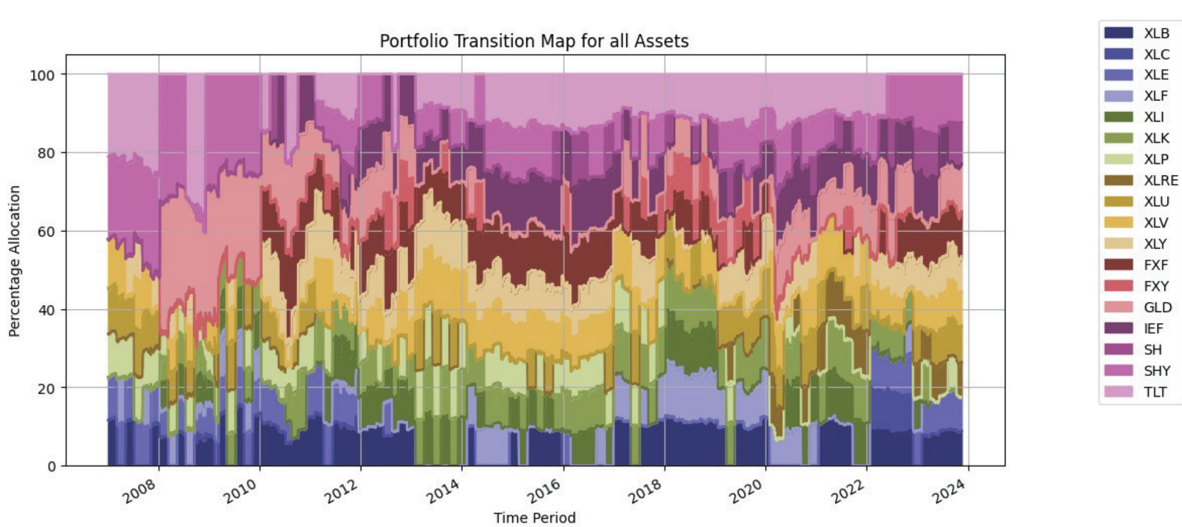
Figure 11. Figure 11. Top plot: Rolling 1Yr. Annualized St. Dev. — Middle plot: Rolling 1Yr. Corr. — Bottom plot: Rolling 1Yr. Beta.

In conclusion, the strategy is characterized by managed volatility, steady market correlation, and a balanced risk profile, appealing to investors with a moderate risk appetite aiming for market alignment.

3.9 Portfolio Agility

This section centers on the dynamic allocation process, illustrated through Figure 12, which charts asset allocation changes from January 2007 to November 2023. This figure highlights the complex shifts in investment strategies and their crucial role in navigating financial market complexities. It aims to elucidate the principles guiding asset allocation decisions and their impact on portfolio performance.

Figure 12. Visual Representation of Strategy Transition: Illustrating Portfolio Rotations.



Asset allocation is depicted as a continuous, dynamic rebalancing effort to leverage market fluctuations while avoiding excessive adjustments that could diminish returns due to transaction fees, set at 10 basis points per trade. Despite the volatility in 2008, leading to 8 rebalancing actions, as indicated by increased color variability in the chart, rebalancing frequency has stabilized at an average of 6 times per year. This demonstrates the portfolio's ability to adapt to market conditions without succumbing to overtrading.

The graphic representation also shows the strategic shifts between various ETFs, marked by color changes, to optimize returns against risk. There's a noticeable shift towards safer assets like SHY in uncertain times, and towards equity ETFs like XLK during periods of market optimism.

In essence, the transition map showcases an active strategy that effectively balances dynamic allocation goals with the need to minimize operational costs, resulting in a portfolio that adeptly responds to market changes while maintaining a prudent rebalancing strategy.

DISCUSSION

This research aims to enhance and broaden the methodologies previously introduced, focusing initially on using LSTM networks for predicting systemic risks and financial crises. LSTM networks have proven effective in analyzing complex economic indicator interactions, providing early detection of crises and essential insights for market participants to take preemptive actions against potential threats.

The next phase will explore topological and geometrical analyses to better understand the complex dynamics of financial markets. Through advanced clustering methods, the research seeks to track market sector progression over time more accurately, enhancing the understanding of market structural changes for improved future trend forecasts and risk or opportunity identification.

Furthermore, the research will extend the use of Explainable Artificial Intelligence to gain a deeper insight into the impact of specific sectors on the market, focusing on analyzing the S&P 500's correlation matrices to pinpoint sectors with significant influence on market conditions.

The study also plans to evaluate other machine learning techniques, such as Generative Pre-trained Transformers (GPT) and reinforcement learning, for their potential contributions. Despite the challenges associated with reinforcement learning, these explorations aim to discover new strategies for financial market analysis and navigation, contributing valuable perspectives and techniques for mitigating financial instability and capturing market opportunities.

CONCLUSIONS

This paper introduces a novel approach in portfolio management, focusing on dynamic asset allocation through the integration of artificial intelligence (AI), specifically Long Short-Term Memory (LSTM) models, with advanced financial analytics to adeptly navigate and exploit market uncertainties. It marks a departure from traditional static strategies, proposing a fluid, data-driven paradigm that utilizes real-time data and predictive analytics to enhance asset allocation and risk-adjusted returns. The proposed model surpasses traditional methods by dynamically adjusting to market conditions, thus effectively managing market volatility risks and aiming for long-term capital growth. Key to this approach is the use of explainable AI frameworks to ensure decision-making is transparent and interpretable.

The model's ability to balance risk and reward, crucial for maintaining robust portfolio performance in diverse market scenarios, is underscored. This is achieved through a blend of spectral analysis of market covariance matrices, sentiment analysis, and investigation into higher-order correlations among asset classes, allowing for a sophisticated understanding of market dynamics and enabling timely portfolio adjustments.

The research highlights the significance of AI and machine learning in advancing financial market applications, suggesting a shift towards more flexible, informed portfolio management strategies. The dynamic asset allocation model addresses the complexities of current financial markets and outlines a framework for ongoing learning and adaptation, essential for achieving sustainable investment success.

In summary, the paper advocates for the adoption of AI-driven dynamic asset allocation strategies in modern portfolio management, which, by leveraging advanced analytics and machine learning, offers the promise of improved returns and enhanced risk management. This research sets the stage for further innovation in financial strategies, indicating a future of sophisticated, adaptable financial management in response to evolving market conditions.

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Trend – Emotion – Timing

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Abstract

There is an antagonism in the market behavior: On a short-term basis prices tend to mean revert while on a medium term a momentum manner can be observed. This has an essential backdrop for any trend-following strategy, since trend-following signals are often triggered in overbought or oversold conditions. This paper provides the statistical evidence of these market characteristics and develops tools to overcome this polarity.

To study the trend-behavior of the markets we need several definitions of "the trend" and use four different technical indicators each with ten varying time-frames. For this set of indicators we explore the nature of trend-following: There is no benefit in conjunction with a time-stop, but there is a value in trend-following in using a counter-signal for exiting. A further analysis proves that the relevance of the momentum-effect is even more evident in the context of benchmarking.

So far we analyzed forty trend-following indicators, but such a big set of indicators is not feasible for an investment approach, since their signals will conflict each other. Therefore we interpret each indicator as one vote in a poll. The result is the Trend-Score and its interpretation is straight-forward: A positive value is linked to an up-trend and the higher its value is, the clearer or stronger is this up-trend. This idea of a Trend-Score is extended to respect several benchmarks.

In the next step we explore the emotions of the investors for a stock, which are usually effected on a short-term basis. We use several technical oscillators on time-frames up to one month to define an Emotion-Index in a similar manner to the Trend-Score. The statistical analysis proves that the ingredients of the *Emotion-Index* are statistically relevant and documents the short-term mean-reverting behavior of the stock market.

So far the short-term mean-reverting and medium-term momentum characteristics of the stock market is described and consistently quantified. To overcome the different market behaviors in the short and medium term, the Anchored-Trend-Score is proposed, which is based on the idea to evaluate the Trend-Score of a stock during least emotional times, hence if the Emotion-Index is close to zero. And of course, the Anchored-Trend-Score considers benchmarks too.

Timing the markets is a challenging task and a general advice is to buy up-trending stocks when their prices correct and are not overbought any more. This recipe can be quantified using the indicators introduced so far: We define the Timing-Indicator as the difference of the Anchored-Trend-Score and the Emotion-Index. The statistical analysis of this so defined Timing-Indicator proves this to be a valuable approach.

There are two applications of these indicators and their statistical properties. The first is dedicated to discretionary investors who want to spot either interesting timing opportunities or the strongest trends in the market. For this purpose we link the preceding results into one graphical representation of the market, a Trend-Emotion-Timing-Chart of the stocks is presented and discussed. This novel chart allows to spot easily opportunities from a timing point of view: Entering into a stock, which has an up-trend but is currently oversold (or vice versa), hence where the absolute value of the Timing-Indicator exceeds the significant threshold of 1.0. On the other hand, the stocks with a clear up- or down-trend can easily be identified, adjusted such that the initial buy-signals do not occur in overbought conditions.

For the second and quantitative application of this research, we reconsider the classical portfolio theory of the Nobel laureates Markowitz and Sharpe. One permanent challenge in applying their theory is to estimate the return of a stock. While usual trend-following approaches overestimate the returns when a stock is overbought (and vice versa), the Anchored-Trend-Score solves this issue – together with the historical volatility of the stock. The consideration of benchmarks, including the benchmark with respect to a risk-free-rate modifies the expression for the Sharpe-ratio, but the fundamentals of the classical approach are unchanged. An example based on the Dow-Jones-Index is shown; and for the sake of a simple example the risk was measured as standard derivation of the portfolio. The concept can easily be generalized to more advanced techniques to quantify the financial risk. Hence a quantitative approach to construct an optimal, trend-following portfolio is established, which does not suffer from the pro-cyclical occurrence of trend signals any more.

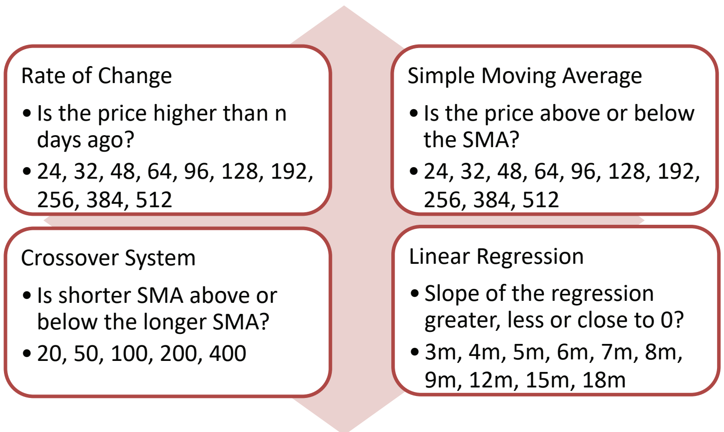
Final remarks on the presented results and ideas for further research complete this paper. In the appendix the statistical results are shown to document the stated market behavior as well as the benefit of the proposed indicators. The basis of this test were the stocks of the S&P 500 index as of 9/30/2024 and the period for all the analysis covers good ten years, more specifically the period from January 2015 to June 2024.

1 Trend

1.1 The technical indicators used

To review the characteristics of trend-following approaches, we define several ways to define a trend. There are plenty methods to do so and for this paper four indicators are selected, each used with ten different timeframes. That is our pool of indicators for the trend analysis (Figure 1). These indicators are well-known and we assign a value of 1.0, if there is a buy signal, a value of -1.0 if there is a sell signal and a value of 0.0 in any other cases or unclear cases, e.g. not enough data, the absolute value of the regression-slope is less than its statistical error.

Figure 1: Overview of the basic trend-following indicators used



The time-frame for the Rate-of-change and the Simple-Moving-Averages are chosen as powers of two or the mean of two adjacent powers of two. The time span (using daily data throughout this paper) ranges from roughly one month up to one and a half year.

1.2 Trend indicators and timing

To test the presented trend-following indicators with respect to their prediction strength, we perform a statistical analysis of each indicator. For each indicator signal at some date it is checked, if the stock was higher or lower after a certain period of time and the return of such a trade measured in terms of

$$ln\left(\frac{Close_{date+period}}{Close_{date}}\right) = ln(Close_{date+period}) - ln(Close_{date})$$

This logarithmic approach to measure the return is used to consider the fact, that a 25% gain is needed to compensate a 20% loss; please recall that $ln(1+0.25) = -ln(1-0.2)$.

The results for the excess probabilities, hence the difference of the probability of a rising stock price depending on the indicator signal being 1.0 or -1.0 are shown in Figure 5. In the most cases, the probability of a profitable long trade is reduced, when a trend-following indicator provides an up-trend signal. That seems counter-intuitive, only for some long-term time-frames there is a positive impact of the trend-following signals.

Looking at the excess returns in the same figure, there is only one data point with a positive excess return at all. The clear conclusion of this analysis is, that trend-following signals are worse for timing – there is no advantage in assuming that a trend will persist at all. We come back later on this and provide a reasonable explanation in section 3.2.

1.3 Trend-following

Do the previous results contradict the thesis of profitable trend-following? Instead of evaluating each indicator signal on its prediction power over a fixed time horizon, we could study the power of each indicator using a simple trading strategy: Just go long, as soon as the indicator signals 1.0 and exit the position, if it is not 1.0 anymore.

The win probability and the average return per trade of this simple trading approach is presented in Figure 6. The probability to win is usually less than 50%, but the average return is positive for each studied indicator. This is the typical characteristics of trend-following trading approach.

A reasoning of the difference to the first analysis is, that in this case the exit is not determined by a fixed time stop, but by a counter-signal of the trend-following indicator. Since the probability of a winning trade is rather small, a fast exit is necessary for an active trend-following investment approach, or as the saying runs: "The trend is your friend until the end!"

1.4 Construction of the Trend-Score

An active investor may choose any of these trend-following strategies, but each will provide different results. The novel idea is to construct a Trend-Score based on our 40 trend-following indicators similar to a poll:

$$TrendScore = \frac{1}{40}\sum_{i=1}^{40} TrendIndicator_i$$

Remember, that the result of each indicator is either -1.0, 1.0 or 0.0. If all Indicators provide a 1.0, hence all votes are in favor of an up-trend, the Trend-Score is 1.0. If all indicators provide -1.0, the resulting Trend-Score is -1.0. And if the indicators provide as much votes in favor for an up-trend as for a down-trend, the Trend-Score computes to 0.0, the result if there is no clear trend at all. Hence the sign of the Trend-Score provides the direction of the trend, and the absolute value its quality.

The advantage of this approach is, that we do not have to decide for a certain kind of trend-following indicator or a fixed time-frame. And such a choice is difficult, since the optimal setup in the past may not be the best setup for the future. Additionally, the change of the Trend-Score is much smoother than just the three states of a single indicator saying long, short, or no position. We will utilize this smoother behavior in the context of Anchoring (section 4) and Portfolio construction (section 7) later in this paper.

2 Benchmarking

An important concept in the investment area is benchmarking, for example the comparison of a single stock with respect to its index. In our examples, we study the stock prices of the constituents of the S&P 500 index; hence we would certainly prefer stocks which outperform this index.

Such benchmarking can be performed by ratio charts. A ratio chart is computed by dividing the close price of the stock for each date by the close price of the index (or any other benchmark). The resulting ratio chart series has no candles anymore, but only close data. But all trend-following indicators are chosen such, that they can also be computed on a ratio chart.

But is trend-following on a ratio chart a suitable approach? In section 1.2 we discussed the timing effect of the trend-following indicators, we present the results of an analogous analysis for the ratio charts in Figure 7. But there is an important difference to observe! The excess probability of an outperformance to persist is higher – especially for shorter time frames. And with regard to the average return of the outperformance, this is increasingly positive over the long run, hence for two or three months in our study. Hence for trend-following, benchmarking with the index provides a considerable benefit!

So the question rises, how can we join the Trend-Score T_1 of a stock itself with the Trend-Score T_2 of the corresponding ratio chart with respect to an index or another benchmark? The idea is quite simple: For a long trade we prefer stock which are in an up-trend and which also outperform the index. Based on this idea we join the two Trend-Scores to a joint Trend-Score T via

$$T := join(T_1, T_2) := sign(T_1, T_2) \cdot min\,(abs(T_1), abs(T_2))$$

In this formula, min denotes the minimum of two numbers, abs denotes the absolute value and sign the common sign of the two numbers, hence

$$sign(T_1, T_2) = \begin{cases} 1.0, \text{ if } T_1 > 0 \text{ and } T_2 > 0 \\ -1.0, \text{ if } T_1 < 0 \text{ and } T_2 < 0 \\ 0.0, \text{ else} \end{cases}$$

One can easily extend this approach to more than one benchmark. For example if one requires that the stock should not only outperform the S&P 500 index, but also its sector index.

3 Emotion

3.1 Emotion-Index

On a short-term basis, usually less than a month, markets often show a mean-reversion pattern which is founded in the emotions of the investors. If the price of a stock has firmly risen over the previous days, the market participants become (too) optimistic about the company. But since all investors bought already, the price will likely consolidate in the near future.

To measure such emotions by technical analysis, oscillators are used to identify overbought or oversold conditions, which reflect the emotions of investors. In order to be independent of a certain time-horizon or measurement approach, again a set of indicators is used as shown in Figure 2. The indicators are rescaled in such a manner, that their codomain is [-1.0 , 1.0] and a value close to -1.0 represents the oversold state and a value close to 1.0 is linked to the overbought state.

The two chosen kinds of oscillators differ in some aspects, so that they complement each other:

- The RSI (Relative Strength Index by Welles Wilder) is calculated on Close data only, but the order of the quotes is essential.
- The Candle Range uses the High and Low of a certain timespan, but the order of the candles in the past is not relevant for the calculation.

Figure 2: Overview of the twelve basic oscillators used

rescaled RSI	• Using 2.0*RSI - 1.0, hence rescale the classical RSI to a codomain of -1.0 to 1.0 • Parameters used are: 5, 8, 11, 14, 17, 20
rescaled CandleRange	• Compute the current close C in relation to the high H_n and low L_n of the last n candles by $2.0\frac{C-L_n}{H_n-L_n} - 1.0$ • Values for n are: 3, 6, 9, 12, 15, 18

Following the lines of the construction of the Trend-Score, we average the twelve oscillators into the Emotion-Index and the resulting value is in the range from -1.0 to 1.0. Again we avoid relying on a particular specification of one certain indicator or time-frame:

$$EmotionIndex = \frac{1}{12}\sum_{i=1}^{12} Oscillator_i$$

To study the predictive properties of the Emotion-Index, we evaluate the Emotion-Index for each stock and date and round the Emotion-Index to the nearest integer multiple of 0.1. The win-probability and the average log return for several time stops are presented in Figure 8. As one can see, the probability for a stock to rise increases for smaller values of the Emotion-Index. This holds for all time-frames, but is even stronger on the shorter ones.

This general anti-cyclical effect also holds for the average log-returns. The lower the value of the Emotion-Index is, the higher is the average return for a fixed-time frame. This data analysis showed clearly that there is indeed a short-term anti-cyclical pattern in the stock market.

3.2 Understanding the worse timing of trend-following

This short-term anti-cyclical pattern in the stock-market can also help to understand the worse timing of the trend-following indicators shown in section 1.2. Even if trend-following works on the long run, the trend-following buy- or sell-signals occur in situations, where the stock is usually overbought or oversold. Hence the short-term anti-cyclical price movements overlay the longer-term trend-following pro-cyclical price pattern. This provides the reasoning of the bad timing of trend-following approaches

This also explains the small win probabilities for any trend-following strategy in general: The trend-following signal for a long-position occurs in an overbought situation and hence a pullback is quite likely. And if this pullback happens just after the trend-signal was triggered, the exit signal might promptly be triggered. Therefore, the entry on a trend-following signal provides no advantage in conjunction with a time-stop.

A closer look to the trend-following signals in Figure 5 showed, that the signals based on linear regression or long-term cross-over signals were not as bad as the other ones. This can also be explained by this emotion-driven behavior of the markets too: These indicators are less influenced by the recent price data and their signals are more stable in the presence of a short-term counter-move of the stock.

Also the effect of benchmarking and trending can be understood by this emotional effect. Since a single stock is likely overbought or oversold if also the index is overbought/sold, the ratio chart is smoother and the anti-cyclical effect is therefore reduced on a ratio chart. This holds even more for the longer-term trend-following indicators as shown in Figure 7.

3.3 Emotion and Benchmarking

Should we consider benchmarking for the Emotion-Index too? The short answer is just: “No”.

Most market participants are emotionally driven by their nominal P&L, and this is the most dominant effect for the emotions of the market participants. Even if an investment manager is compared to the index, he or she would certainly not party on an outperformance with respect to the index, because this performance will undermine the assets under management. At least I haven’t heard someone saying: “I am very excited on my x% loss on some stock, because it outperformed the index”

4 Anchoring

We learned that the short-term emotional behavior in the market offsets any trend-following approach. To overcome this issue, an anchoring is proposed. The idea behind this anchoring is quite simple: It is a wise advise in general not to decide on something, while you are too emotionally involved in a matter. Applying this concept to the Trend-Score, we should not validate it in a highly emotional state. Hence we should decide on the trend only, when the Emotion-Index is close to zero. For practical purposes, the Trend-Score is evaluated whenever the Emotion-Index changes its sign — and the Anchored-Trend-Score remains constant otherwise. Hence this Anchored-Trend-Score is anchored to times with least emotional sentiment, or while the market-participants have the most rational view on the markets.

We use the same approach as before to test the anchored trend signals, where the Anchored-Trend-Score is also based on benchmarking with respect to the S&P500 index. The results are shown in Figure 9. Clearly, for each time stop maturity, as well the hit probability as the average log-return is increasing with the anchored trend. Hence a higher value of the anchored trend provides an essential statistical advantage for positive stock price returns.

5 Timing

A general advise for active investment is to look for a correction in an existing trend. This approach can be utilized with the indicators presented so far. For a long position, one would like to have an uptrend, hence a rather high Anchored-Trend-Score, and at the same time also an oversold condition, hence a rather negative Emotion-Index. Therefore we introduce the Timing-Indicator as the difference of the Anchored-Trend-Score and the Emotion:

$$\mathit{TimingIndicator} = \mathit{AnchoredTrendScore} - \mathit{EmotionIndex}$$

The codomain for the Timing-Indicator is clearly given by -2.0 to 2.0. A good timing value for a long position is above 1.0 and a good timing value for a short position is below -1.0. This is statistically validated in Figure 10, again as well for the win probability as for the average log-return and is valid for all considered timeframes.

For an active investor, sorting the stocks by the value of the Timing-Indicator helps to find interesting swing trading candidates — as well on the long as on the short side. On one side of the list you find oversold stocks in an up-trend, and on the other side there are the overbought stocks in a down-trend.

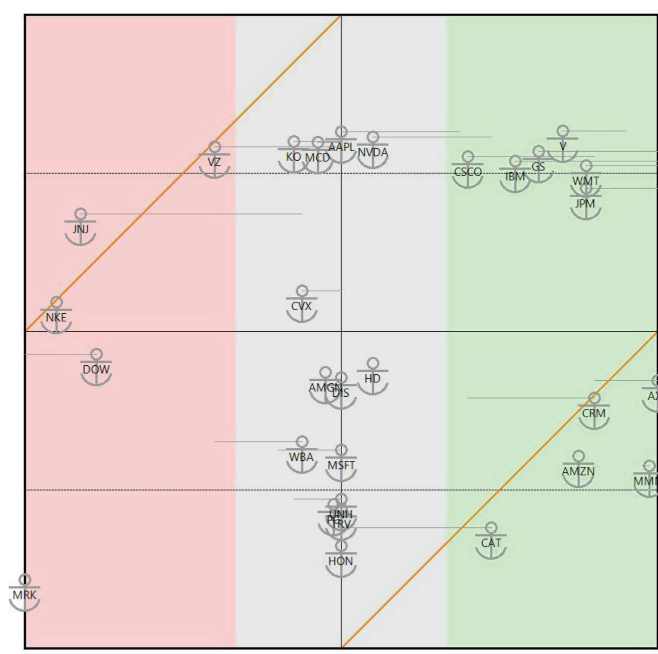
6 Charting

So far we introduced the Trend-Score (Plain and Anchored, possibly with benchmarking), the Emotion-Index and the Timing-Indicator. How to present all this information in one chart? Following the idea, that there is not a stock market, but a market of stocks, we can plot each stock in the two-dimensional plane: The x-coordinate is the Anchored-Trend-Score and the y-coordinate is the Emotion-Index.

To illustrate the idea, a chart based on the Dow-Jones-Industrial-Average constituents is shown in Figure 3. Each stock is represented by an anchor (to remind to the anchored trend) with the ring representing the actual position. Attached to the ring there is a horizontal line (rope), pointing to the current position of the Trend-Score, hence showing the position of the current Trend-Score. The size of the stock of the anchor represents the minimum movement of the Trend-Score to the left or right, hence representing the size of 2 * 1/40. Below the stock of each anchor, the ticker symbol of the stock is printed.

The red shared area represents the area of down-trends (Anchored-Trend-Score <-1/3) and the green area the area of up-trends (Anchored-Trend-Score > 1/3). The two golden lines represents the line where the timing indicator is either -1.0 (in the top left section) or 1.0 (in the bottom right section).

Figure 3: Trend-Emotion-Timing-Chart (Tremti-Chart) of the Dow constituents as of (Feb 14, 2025)



We explain the proposed representation by the example in Figure 3: In this chart, the stocks of JNJ, NKE, VZ might be good candidates to short (overbought in a down-trend). There are in total eleven stocks in a clear uptrend (green area), of which six are overbought and hence an active investor would trim these positions (CSCO, IBM, GS, V, WMT, JPM). And there are five stocks in the lower right triangle which indicates good buying opportunities (CRM, CAT, AMZN, MMM, AXP). Of these five positions, there is a warning on CRM and CAT: These anchors have a long line to the left, indicating that the current trend score is much weaker than the anchored trend. An active investor aiming for only a few buying opportunities would therefore favor AXP, AMZN and MMM in the provided example.

There are lots of anchors at or close to the vertical no-trend-line in the mid. This is the effect of the benchmarking with the Dow Jones Industrial Average index. Hence these are the stocks, which have an up-trend ("Trend-Score" ≥ 0.0), but the ratio chart of the stock compared to the index has a negative (or zero) Trend-Score. Hence these are the boring stocks from a trend-follower's point of view.

7 Portfolio construction

The previous approach provides by one chart an overview of rewarding investment ideas. Now we aim to construct a portfolio composition quantitatively. In the classical portfolio theory based on the famous work of the Nobel laureates Harry Markowitz and William Sharpe, there is a big challenge to estimate the expected return of a stock. Any classical trend-following return estimation fails in this respect due to the negative effect of the pro-cyclical signal generation. We can now overcome this issue based on the Anchored-Trend-Score.

7.1 Estimation of the equity return

We have already shown the positive correlation between Anchored-Trend-Score and future returns of a stock and that this indicator overcomes the pro-cyclical market behavior due to the mean-reversion behavior of prices on a short time frame by construction. So this is one factor to consider for the return estimation.

Given two stocks with the same Anchored-Trend-Score, but one of these stocks is more volatile, one would expect a higher return on the more volatile stock. To estimate the volatility, we advise to use the historical volatility since it is less erratic than the implied volatility; and the historical volatility is also available for equities without (a liquid) option market. So as a rule of thumb, the return of a stock for portfolio optimization could be estimated by

Return ≈ Volatility · AnchoredTrendScore

Hence the size of the return is proportional to the volatility of the stock, but also the Anchored-Trend-Score is involved: By this construction the return estimation is not pro-cyclical anymore and the estimated return is negative in down-trends. Furthermore, also the consideration of benchmarks (e.g. the S&P 500 index) can be utilized in this definition as explained earlier. And by using the historical volatility and the Anchored-Trend-Score, only price information is used to estimate the return — a very unbiased approach for an active investor.

7.2 Realigning the Portfolio Optimization

To construct an optimized portfolio similar to the classical portfolio theory, we are searching for the portfolio weights w_i with the boundary condition $\sum_{i=1}^{N} w_i = 1.0$ and we avoid short-selling by imposing $w_i \geq 0$. The return R_i of each stock is given by the product of the volatility and its Anchored-Trend-Score. Note that the Anchored-Trend-Score can consider any benchmarks, including a benchmark based on a risk-free interest rate. Therefore the return should be interpreted as excess return and the objective function to optimize is similar to the Sharpe ratio, note that there is no subtraction of the risk-free rate in the nominator anymore:

$$T(\omega) = \frac{\sum_{i=1}^{N} \omega_i R_i}{Risk(\omega)}$$

This approach facilitates the usage of any risk measure (e.g. the expected shortfall), for the purpose of a simple demonstration we will use the standard derivation in this paper, where C denotes the covariance matrix of the stocks and the portfolio risk is hence given by:

$$Risk(\omega) = \sqrt{\sum_{i=i}^{N} \sum_{j=1}^{N} C_{i\,j}\, \omega_i\, \omega_j}$$

The optimization of $T(\omega)$ under the constraints on ω is a well-formed problem: A linear optimization over a convex set. There are several approaches to solve this problem, for example this can be achieved by a Simulated Annealing.

7.3 Example

To illustrate the optimal portfolio composition we perform this optimization for a portfolio of stocks in the Dow-Jones based on the example presented in section 6. Since we only like stocks with a positive Anchored-Trend-Score, the selection of instruments is reduced and the optimal weights are shown in the last column in Figure 4. To perform the risk measurement by the estimated volatility of the portfolio, the correlations of the stocks on a weekly basis over the last year have been utilized to build the covariance matrix.

Figure 4: Example of an optimal portfolio of Dow Jones stocks

Ticker	Anchored Trend	Volatility	Est. Return	Weight
AXP	100%	26,6%	26,6%	10,7%
MMM	98%	34,3%	33,4%	17,0%
CRM	80%	42,1%	33,7%	9,5%
JPM	78%	26,7%	20,7%	8,3%
WMT	78%	20,4%	15,8%	22,9%
AMZN	75%	31,0%	23,2%	18,4%
V	70%	18,8%	13,2%	13,2%
GS	63%	29,6%	18,5%	0,0%
IBM	55%	28,4%	15,6%	0,0%
CAT	48%	30,0%	14,2%	0,0%
CSCO	40%	20,1%	8,0%	0,0%
HD	10%	22,7%	2,3%	0,0%
NVDA	10%	61,8%	6,2%	0,0%
Optimized Portfolio		**15,4%**	**21,3%**	**100,0%**

The result of the optimization shows that the optimal portfolio has a reduced volatility compared to each stock and an estimated return higher than the average. That is the usual result of any mathematical portfolio optimization. This example also shows, that stocks with a quite low Anchored Trend, hence a low estimated Return by this approach, will not be included in the optimized portfolio — only the stocks in the green area of Figure 3 has been selected into the portfolio in this example!

This is the optimized portfolio for a trend-following investor who avoids the short-term disadvantages of the pro-cyclical signals of trend-following indicators, since the Anchoring is an essential part of this enhancement of the classical portfolio theory.

8 Conclusion

The first novel idea of this paper is to overcome choosing a precise time-horizon in the calculation of the Trend-Score or the Emotion-Index by averaging over a set of established trend-following indicators or oscillators using several time-frames. It's not about getting the right indicator for the correct time-frame anymore, but the general behavior of the market: Short term movements up to a month are more likely mean-reverting, while medium term movements from a month up to two years are leaning more to keep their momentum. This general pattern of the stock market is confirmed by statistics based on a ten year history of the constituents of the S&P 500. Furthermore is shown in the paper that benchmarking contributes essentially to trend-following strategies, hence the benchmarking is also covered in the computation of the Trend-Score.

The antagonism of emotion and trend yields to the second finding: For trend-following we could affirm that anchoring the trend to a less emotional time in the market gives an additional edge — hence the Anchored-Trend-Score is established. The discussed opposition of trend and emotion is mathematical expressed in the Timing-Indicator, which is trend minus emotion.

To complement the paper, two applications of the discussed indicators are presented. A novel charting is proposed to overview the stocks of a market, by plotting each stock on a [-1 to 1] x [-1 to 1] square. Only one glance is needed to identify the trending stocks, or the stocks being overbought or oversold. Additionally, two diagonal lines mark the area of stocks having an interesting setup from a timing perspective, which could be utilized for swing-trading. The presentation of the Timing-Indicator establishes also the opportunity for further research, e.g. the development and backtest of a precise trading strategy which is based on it.

Another application of the Anchored-Trend-Score persists in the estimation of the return of a stock, together with its volatility. Since classical approaches of trend-following portfolio constructions suffer from the pro-cyclical signaling of trend-following indicators, the Anchored-Trend-Score can overcome this issue. The well-known portfolio optimization can easily be extended to this approach. We constructed a trend-following portfolio optimization without being negatively exposed to the short-term, emotionally driven price action of the market. This approach to optimize a portfolio can easily be adapted to more advanced measures of risk e.g. the Value-at-Risk used for regulatory purposes, or the (coherent risk measure) Expected Shortfall (see Reiss, *The Coherent Market Portfolio*, IFTA Journal 2019).

So this paper demonstrates two essential drivers of the stock market: The short-term Emotion and the medium-term Trend and the paper establishes tools to overcome their antagonism. It proposes a novel graphical overview (Tremti-Chart) for an active discretionary investor and provides a coherent portfolio construction for the quantitative investment manager.

Market data

The market data for the presented analysis has been obtained through the software TAI-PAN from the provider Lenz+Partner GmbH (www.lp-software.de), which is part of Infront ASA (www.infrontfinance.com).

9 Appendix Statistical data

9.1 Trend with time stop

Figure 5: Excess profit probability and log-return of trend-following indicators

Indicator	Exxcess Probability						Exxcess (log) Return					
Time stop horizon	1 w	2 w	3 w	1 m	2 m	3 m	1 w	2 w	3 w	1 m	2 m	3 m
RoC(24)	-0,6%	-1,4%	-1,6%	-2,3%	-3,1%	-3,1%	-0,1%	-0,2%	-0,3%	-0,7%	-1,3%	-1,4%
RoC(32)	-1,3%	-1,9%	-2,1%	-2,6%	-3,0%	-3,4%	-0,1%	-0,3%	-0,4%	-0,8%	-1,4%	-1,5%
RoC(48)	-1,3%	-2,3%	-2,5%	-2,9%	-3,2%	-3,2%	-0,2%	-0,3%	-0,6%	-1,0%	-1,4%	-1,7%
RoC(64)	-0,9%	-2,1%	-1,9%	-2,3%	-3,0%	-2,3%	-0,2%	-0,4%	-0,5%	-0,8%	-1,4%	-1,4%
RoC(96)	-1,4%	-2,3%	-2,0%	-2,1%	-2,1%	-2,0%	-0,2%	-0,3%	-0,5%	-0,8%	-1,1%	-1,1%
RoC(128)	0,0%	-1,1%	-1,0%	-1,5%	-2,0%	-1,4%	-0,1%	-0,2%	-0,4%	-0,6%	-0,9%	-0,8%
RoC(192)	0,2%	-0,5%	-0,1%	-0,5%	-0,8%	-1,1%	-0,1%	-0,2%	-0,3%	-0,5%	-0,7%	-0,8%
RoC(256)	0,1%	-0,6%	-0,7%	-1,5%	-2,2%	-3,3%	-0,1%	-0,2%	-0,4%	-0,6%	-1,1%	-1,6%
RoC(384)	0,1%	-0,7%	-0,8%	-1,8%	-3,0%	-3,7%	-0,1%	-0,3%	-0,4%	-0,7%	-1,2%	-1,6%
RoC(512)	-0,1%	-0,7%	-1,0%	-2,2%	-3,7%	-4,3%	-0,2%	-0,3%	-0,5%	-0,8%	-1,4%	-1,8%
SMA(24)	-0,8%	-1,2%	-1,0%	-2,0%	-3,3%	-3,1%	-0,1%	-0,1%	-0,3%	-0,6%	-1,4%	-1,6%
SMA(32)	-1,0%	-1,6%	-1,5%	-2,5%	-3,5%	-3,5%	-0,1%	-0,2%	-0,4%	-0,7%	-1,6%	-1,7%
SMA(48)	-1,0%	-1,7%	-1,8%	-2,8%	-3,5%	-3,7%	-0,1%	-0,2%	-0,5%	-0,9%	-1,6%	-1,8%
SMA(64)	-1,1%	-2,0%	-2,1%	-3,0%	-3,6%	-3,6%	-0,2%	-0,3%	-0,6%	-1,0%	-1,7%	-1,9%
SMA(96)	-1,2%	-2,3%	-2,4%	-3,0%	-3,4%	-3,0%	-0,2%	-0,4%	-0,6%	-1,0%	-1,6%	-1,7%
SMA(128)	-0,9%	-2,0%	-1,9%	-2,3%	-2,9%	-2,5%	-0,1%	-0,3%	-0,5%	-0,9%	-1,4%	-1,4%
SMA(192)	-0,4%	-1,4%	-1,2%	-1,6%	-2,0%	-1,9%	-0,1%	-0,3%	-0,4%	-0,7%	-1,1%	-1,2%
SMA(256)	-0,1%	-1,1%	-0,9%	-1,4%	-1,7%	-1,9%	-0,1%	-0,2%	-0,4%	-0,6%	-1,0%	-1,2%
SMA(384)	-0,3%	-1,3%	-1,3%	-2,1%	-2,6%	-3,0%	-0,1%	-0,3%	-0,5%	-0,8%	-1,2%	-1,5%
SMA(512)	-0,3%	-1,4%	-1,5%	-2,6%	-3,4%	-3,8%	-0,2%	-0,4%	-0,6%	-0,9%	-1,4%	-1,7%
Crossover(20, 400)	-0,3%	-1,2%	-1,2%	-1,8%	-2,2%	-2,5%	-0,2%	-0,3%	-0,5%	-0,7%	-1,0%	-1,2%
Crossover(50, 400)	0,1%	-0,4%	-0,3%	-0,9%	-1,4%	-1,8%	-0,1%	-0,2%	-0,4%	-0,5%	-0,7%	-1,0%
Crossover(100, 400)	0,6%	0,5%	0,5%	-0,1%	-1,0%	-1,6%	-0,1%	-0,1%	-0,2%	-0,3%	-0,6%	-0,8%
Crossover(200, 400)	0,7%	0,5%	0,2%	-0,6%	-1,8%	-3,1%	-0,1%	-0,2%	-0,3%	-0,4%	-0,8%	-1,2%
Crossover(20, 200)	-0,6%	-1,7%	-1,6%	-1,8%	-1,6%	-1,5%	-0,2%	-0,3%	-0,5%	-0,7%	-0,9%	-0,9%
Crossover(50, 200)	-0,3%	-0,9%	-0,6%	-0,8%	-1,1%	-0,4%	-0,1%	-0,3%	-0,4%	-0,5%	-0,6%	-0,4%
Crossover(100, 200)	0,3%	0,1%	0,5%	0,5%	0,3%	0,7%	-0,1%	-0,1%	-0,1%	-0,1%	-0,1%	0,1%
Crossover(20, 100)	-1,3%	-2,8%	-2,9%	-3,2%	-2,5%	-2,2%	-0,2%	-0,4%	-0,7%	-1,0%	-1,3%	-1,2%
Crossover(50, 100)	-1,0%	-1,9%	-1,7%	-1,7%	-1,7%	-0,7%	-0,2%	-0,4%	-0,5%	-0,7%	-0,9%	-0,7%
Crossover(20, 50)	-1,1%	-2,5%	-2,9%	-3,5%	-3,0%	-3,2%	-0,1%	-0,4%	-0,6%	-1,0%	-1,4%	-1,5%
LinearReg(3)	-1,7%	-3,1%	-3,2%	-3,4%	-3,2%	-2,7%	-0,3%	-0,5%	-0,8%	-1,1%	-1,5%	-1,5%
LinearReg(4)	-1,3%	-2,5%	-2,5%	-2,8%	-2,5%	-1,5%	-0,2%	-0,4%	-0,6%	-0,9%	-1,3%	-1,1%
LinearReg(5)	-1,2%	-2,2%	-1,9%	-1,9%	-1,7%	-0,9%	-0,2%	-0,4%	-0,6%	-0,7%	-0,9%	-0,7%
LinearReg(6)	-0,4%	-1,3%	-1,0%	-1,1%	-1,4%	-0,5%	-0,2%	-0,3%	-0,4%	-0,6%	-0,7%	-0,4%
LinearReg(7)	-0,5%	-1,3%	-1,1%	-1,1%	-1,0%	-0,1%	-0,2%	-0,3%	-0,4%	-0,5%	-0,4%	-0,2%
LinearReg(8)	-0,1%	-0,7%	-0,3%	-0,3%	-0,3%	0,3%	-0,1%	-0,2%	-0,2%	-0,3%	-0,3%	-0,1%
LinearReg(9)	0,2%	-0,2%	0,2%	0,0%	-0,1%	0,3%	-0,1%	-0,2%	-0,2%	-0,3%	-0,3%	-0,2%
LinearReg(12)	0,6%	0,5%	0,7%	0,2%	-0,4%	-1,1%	-0,1%	-0,1%	-0,2%	-0,2%	-0,4%	-0,7%
LinearReg(15)	0,4%	0,1%	-0,1%	-0,8%	-1,8%	-2,8%	-0,1%	-0,2%	-0,3%	-0,5%	-0,9%	-1,3%
LinearReg(18)	0,6%	0,2%	0,0%	-0,9%	-2,0%	-3,1%	-0,1%	-0,2%	-0,3%	-0,5%	-0,9%	-1,3%

9.2 Pure Trend-following

Figure 6: A simple long-only trend-following strategy for several indicators

Indicator	Win probability	Avg. log return
RoC(24)	36,3%	0,3%
RoC(32)	35,6%	0,3%
RoC(48)	36,7%	0,4%
RoC(64)	35,3%	0,4%
RoC(96)	33,6%	0,5%
RoC(128)	35,4%	0,9%
RoC(192)	34,9%	1,1%
RoC(256)	34,4%	1,2%
RoC(384)	33,9%	1,4%
RoC(512)	33,7%	1,6%
SMA(24)	35,1%	0,2%
SMA(32)	33,7%	0,3%
SMA(48)	31,6%	0,3%
SMA(64)	29,9%	0,4%
SMA(96)	28,1%	0,4%
SMA(128)	26,8%	0,6%
SMA(192)	25,5%	0,9%
SMA(256)	25,0%	1,1%
SMA(384)	23,4%	1,2%
SMA(512)	22,3%	1,3%
Crossover(20, 400)	33,3%	4,1%
Crossover(50, 400)	42,4%	6,7%
Crossover(100, 400)	50,3%	10,0%
Crossover(200, 400)	53,8%	11,4%
Crossover(20, 200)	35,9%	2,9%
Crossover(50, 200)	43,3%	4,3%
Crossover(100, 200)	51,3%	6,2%
Crossover(20, 100)	38,6%	1,6%
Crossover(50, 100)	44,1%	1,9%
Crossover(20, 50)	43,0%	1,2%
LinearReg(3)	39,9%	0,9%
LinearReg(4)	42,1%	1,6%
LinearReg(5)	42,3%	2,1%
LinearReg(6)	43,6%	3,2%
LinearReg(7)	44,4%	3,7%
LinearReg(8)	46,7%	4,9%
LinearReg(9)	47,3%	6,1%
LinearReg(12)	50,2%	8,6%
LinearReg(15)	49,0%	8,8%
LinearReg(18)	50,7%	11,0%

9.3 Ratio-Trend — Benchmarking with Index

Figure 7: Excess profit probability and excess log-return of several trend-following indicators applied to the ratio chart (benchmarking)

Indicator	Exxcess Probability						Exxcess (log) Return					
Time stop horizon	1 w	2 w	3 w	1 m	2 m	3 m	1 w	2 w	3 w	1 m	2 m	3 m
RoC(24)	-0,3%	-0,6%	-0,7%	-1,1%	-1,1%	-0,9%	0,0%	-0,1%	-0,1%	-0,2%	-0,3%	-0,2%
RoC(32)	-0,3%	-0,4%	-0,3%	-0,7%	-1,1%	-0,7%	0,0%	0,0%	-0,1%	-0,2%	-0,3%	-0,1%
RoC(48)	0,0%	-0,1%	-0,2%	-0,7%	-0,3%	-0,1%	0,0%	0,0%	-0,1%	-0,2%	-0,1%	0,0%
RoC(64)	0,0%	-0,2%	-0,1%	-0,2%	-0,3%	0,2%	0,0%	0,0%	0,0%	-0,1%	0,0%	0,2%
RoC(96)	0,3%	0,1%	0,2%	0,1%	0,5%	0,5%	0,0%	0,0%	0,0%	0,0%	0,2%	0,3%
RoC(128)	1,3%	1,2%	1,3%	1,0%	0,9%	0,7%	0,1%	0,1%	0,1%	0,1%	0,3%	0,4%
RoC(192)	1,2%	1,0%	1,1%	1,0%	1,2%	1,0%	0,0%	0,1%	0,1%	0,2%	0,4%	0,6%
RoC(256)	1,4%	1,2%	1,1%	1,0%	0,4%	0,0%	0,0%	0,1%	0,1%	0,2%	0,3%	0,4%
RoC(384)	1,6%	1,5%	1,5%	1,2%	0,6%	0,3%	0,0%	0,1%	0,1%	0,1%	0,3%	0,4%
RoC(512)	1,6%	1,6%	1,6%	1,3%	0,5%	0,0%	0,0%	0,1%	0,1%	0,1%	0,1%	0,2%
SMA(24)	-0,5%	-0,6%	-0,5%	-1,0%	-1,0%	-0,9%	0,0%	-0,1%	-0,1%	-0,2%	-0,3%	-0,3%
SMA(32)	-0,4%	-0,5%	-0,5%	-1,0%	-1,1%	-0,9%	0,0%	-0,1%	-0,1%	-0,2%	-0,3%	-0,2%
SMA(48)	-0,2%	-0,3%	-0,3%	-0,9%	-1,1%	-0,7%	0,0%	-0,1%	-0,1%	-0,2%	-0,3%	-0,1%
SMA(64)	-0,1%	-0,3%	-0,3%	-0,8%	-0,8%	-0,4%	0,0%	-0,1%	-0,1%	-0,2%	-0,2%	-0,1%
SMA(96)	0,1%	-0,1%	0,0%	-0,4%	-0,1%	0,3%	0,0%	0,0%	0,0%	-0,1%	0,0%	0,2%
SMA(128)	0,3%	0,2%	0,3%	0,1%	0,4%	0,5%	0,0%	0,0%	0,0%	0,0%	0,1%	0,3%
SMA(192)	0,8%	0,7%	0,7%	0,6%	0,7%	0,6%	0,0%	0,1%	0,1%	0,1%	0,3%	0,4%
SMA(256)	1,2%	1,1%	1,1%	1,0%	0,9%	0,6%	0,0%	0,1%	0,1%	0,2%	0,3%	0,5%
SMA(384)	1,4%	1,2%	1,3%	1,2%	1,1%	0,8%	0,0%	0,1%	0,1%	0,2%	0,4%	0,5%
SMA(512)	1,5%	1,4%	1,4%	1,1%	0,9%	0,6%	0,0%	0,1%	0,1%	0,2%	0,3%	0,5%
Crossover(20, 400)	1,7%	1,5%	1,5%	1,3%	1,1%	0,9%	0,1%	0,1%	0,2%	0,2%	0,4%	0,6%
Crossover(50, 400)	1,8%	1,5%	1,5%	1,3%	0,9%	0,9%	0,1%	0,1%	0,2%	0,2%	0,4%	0,6%
Crossover(100, 400)	1,7%	1,4%	1,3%	1,2%	0,7%	0,5%	0,1%	0,1%	0,1%	0,2%	0,4%	0,5%
Crossover(200, 400)	1,6%	1,3%	1,3%	1,1%	0,3%	0,1%	0,0%	0,1%	0,1%	0,2%	0,3%	0,4%
Crossover(20, 200)	1,0%	0,9%	0,9%	0,8%	0,9%	0,7%	0,0%	0,1%	0,1%	0,1%	0,3%	0,5%
Crossover(50, 200)	1,3%	1,2%	1,2%	1,1%	1,0%	0,8%	0,1%	0,1%	0,1%	0,2%	0,4%	0,5%
Crossover(100, 200)	1,3%	1,2%	1,2%	1,1%	1,1%	0,5%	0,0%	0,1%	0,1%	0,2%	0,4%	0,4%
Crossover(20, 100)	0,1%	-0,1%	-0,2%	-0,4%	0,3%	0,7%	0,0%	0,0%	0,0%	0,0%	0,1%	0,3%
Crossover(50, 100)	0,5%	0,4%	0,4%	0,4%	0,7%	0,9%	0,0%	0,0%	0,1%	0,1%	0,3%	0,4%
Crossover(20, 50)	-0,2%	-0,5%	-0,6%	-1,1%	-0,5%	-0,2%	0,0%	-0,1%	-0,1%	-0,2%	-0,2%	0,0%
LinearReg(3)	-0,2%	-0,5%	-0,5%	-0,6%	0,0%	0,4%	0,0%	-0,1%	-0,1%	-0,1%	0,0%	0,2%
LinearReg(4)	0,4%	0,3%	0,2%	0,1%	0,3%	0,8%	0,0%	0,0%	0,0%	0,0%	0,2%	0,4%
LinearReg(5)	0,6%	0,5%	0,5%	0,5%	0,8%	0,8%	0,0%	0,1%	0,1%	0,1%	0,3%	0,4%
LinearReg(6)	1,2%	1,1%	1,2%	1,1%	1,0%	0,8%	0,0%	0,1%	0,1%	0,2%	0,3%	0,5%
LinearReg(7)	1,4%	1,3%	1,3%	1,1%	1,0%	0,8%	0,1%	0,1%	0,1%	0,2%	0,3%	0,5%
LinearReg(8)	1,4%	1,3%	1,3%	1,1%	1,0%	0,7%	0,1%	0,1%	0,1%	0,2%	0,4%	0,5%
LinearReg(9)	1,4%	1,3%	1,2%	1,1%	1,1%	0,7%	0,0%	0,1%	0,1%	0,2%	0,4%	0,5%
LinearReg(12)	1,6%	1,3%	1,2%	1,1%	0,6%	0,0%	0,1%	0,1%	0,2%	0,2%	0,4%	0,5%
LinearReg(15)	1,6%	1,2%	1,2%	0,9%	0,1%	-0,2%	0,0%	0,1%	0,1%	0,1%	0,3%	0,4%
LinearReg(18)	1,7%	1,5%	1,5%	1,3%	0,5%	0,4%	0,0%	0,1%	0,1%	0,2%	0,3%	0,4%

9.4 Emotions and time stop

Figure 8: Profit probabilities and average log-returns by Emotion

Emotion	Profit Probability						Average (log) Return					
Time stop horizon	1 w	2 w	3 w	1 m	2 m	3 m	1 w	2 w	3 w	1 m	2 m	3 m
-1,0	89%	78%	81%	84%	84%	81%	3,0%	3,6%	5,8%	8,7%	11%	8,9%
-0,9	61%	61%	62%	62%	63%	66%	0,4%	0,1%	0,4%	1,5%	3,2%	5,7%
-0,8	56%	57%	57%	58%	61%	63%	0,3%	0,1%	0,1%	0,9%	2,4%	3,9%
-0,7	55%	57%	57%	57%	61%	62%	0,2%	0,4%	0,5%	1,0%	2,4%	3,6%
-0,6	55%	56%	56%	57%	60%	62%	0,3%	0,5%	0,7%	1,1%	2,3%	3,3%
-0,5	55%	56%	56%	57%	60%	61%	0,3%	0,4%	0,7%	1,0%	2,2%	3,1%
-0,4	55%	56%	57%	57%	60%	61%	0,3%	0,5%	0,7%	1,1%	2,1%	3,0%
-0,3	55%	56%	56%	57%	59%	61%	0,3%	0,4%	0,7%	1,0%	1,9%	2,8%
-0,2	54%	55%	56%	56%	59%	60%	0,2%	0,4%	0,6%	0,9%	1,8%	2,5%
-0,1	54%	55%	56%	57%	59%	60%	0,2%	0,4%	0,6%	0,9%	1,7%	2,4%
0,0	54%	55%	56%	56%	58%	60%	0,2%	0,4%	0,6%	0,8%	1,6%	2,2%
0,1	54%	55%	56%	56%	58%	60%	0,2%	0,4%	0,5%	0,8%	1,5%	2,0%
0,2	54%	55%	56%	57%	58%	60%	0,2%	0,4%	0,6%	0,8%	1,4%	2,0%
0,3	54%	55%	56%	56%	58%	59%	0,1%	0,3%	0,5%	0,6%	1,2%	1,8%
0,4	54%	55%	56%	56%	58%	59%	0,1%	0,3%	0,4%	0,6%	1,1%	1,8%
0,5	54%	55%	56%	56%	57%	59%	0,1%	0,2%	0,4%	0,5%	0,9%	1,6%
0,6	53%	54%	55%	56%	57%	58%	0,1%	0,2%	0,3%	0,5%	0,7%	1,4%
0,7	53%	55%	55%	55%	56%	58%	0,0%	0,2%	0,2%	0,3%	0,5%	1,2%
0,8	52%	54%	55%	54%	55%	57%	0,0%	0,2%	0,2%	0,1%	0,1%	1,0%
0,9	50%	53%	54%	53%	54%	58%	-0,2%	0,0%	0,1%	-0,2%	-0,3%	0,9%
1,0	41%	44%	47%	53%	57%	56%	-0,6%	-0,7%	-0,1%	-0,1%	-0,8%	-0,2%

9.5 Anchored-Trend-Score

Figure 9: Profit probabilities and average log-returns by the anchored trend

Anchored Trend Score	Profit Probability							Average (log) Return					
Time stop horizon	1 w	2 w	3 w	1 m	2 m	3 m		1 w	2 w	3 w	1 m	2 m	3 m
-1,0	48%	47%	47%	48%	49%	48%		-0,2%	-0,4%	-0,6%	-0,6%	-0,9%	-1,2%
-0,9	49%	50%	50%	50%	51%	52%		-0,2%	-0,4%	-0,5%	-0,5%	-0,5%	-0,6%
-0,8	52%	52%	52%	52%	54%	54%		0,1%	0,1%	0,1%	0,0%	0,1%	0,0%
-0,7	49%	50%	51%	49%	51%	52%		-0,2%	-0,2%	-0,1%	-0,3%	-0,6%	-0,3%
-0,6	52%	51%	52%	52%	52%	53%		-0,1%	-0,1%	0,0%	-0,2%	-0,2%	0,0%
-0,5	52%	53%	52%	51%	53%	53%		0,0%	0,0%	-0,1%	-0,1%	-0,1%	0,3%
-0,4	53%	52%	52%	52%	53%	54%		0,0%	0,0%	0,0%	-0,1%	0,0%	0,4%
-0,3	53%	53%	53%	52%	54%	55%		0,0%	0,0%	0,1%	0,1%	0,3%	0,5%
-0,2	52%	52%	52%	52%	54%	56%		0,0%	0,0%	0,0%	0,0%	0,5%	0,7%
-0,1	52%	52%	51%	52%	54%	56%		0,0%	0,0%	0,0%	0,1%	0,4%	0,8%
0,0	54%	55%	55%	55%	57%	59%		0,1%	0,2%	0,4%	0,4%	1,0%	1,5%
0,1	55%	56%	56%	56%	57%	57%		0,2%	0,4%	0,6%	0,7%	1,1%	1,5%
0,2	55%	55%	55%	55%	56%	57%		0,2%	0,3%	0,5%	0,8%	1,1%	1,5%
0,3	54%	56%	56%	57%	57%	58%		0,2%	0,4%	0,5%	0,7%	0,9%	1,4%
0,4	53%	54%	54%	54%	55%	57%		0,1%	0,2%	0,3%	0,5%	0,9%	1,4%
0,5	53%	54%	54%	55%	56%	56%		0,2%	0,2%	0,4%	0,6%	0,9%	1,1%
0,6	54%	55%	54%	54%	56%	57%		0,1%	0,3%	0,4%	0,4%	0,9%	1,3%
0,7	54%	54%	55%	55%	57%	59%		0,1%	0,3%	0,5%	0,7%	1,2%	1,8%
0,8	55%	56%	56%	56%	57%	57%		0,3%	0,5%	0,6%	0,7%	1,0%	1,4%
0,9	55%	56%	57%	56%	56%	56%		0,2%	0,4%	0,5%	0,6%	0,8%	1,1%
1,0	57%	58%	59%	58%	58%	60%		0,4%	0,8%	1,0%	1,1%	1,7%	2,2%

9.6 Statistics of the Timing-Indicator

Figure 10: Profit Probabilities and average (log) return of a rising stock depending on the Timing-Indicator

Timing-Indicator	Profit Probability							Average (log) Return					
Time stop horizon	1 w	2 w	3 w	1 m	2 m	3 m		1 w	2 w	3 w	1 m	2 m	3 m
-1,8	50%	54%	54%	55%	55%	57%		-0,3%	0,6%	0,4%	0,3%	-0,6%	-0,5%
-1,7	50%	56%	55%	54%	56%	57%		-0,1%	0,6%	0,5%	0,4%	0,5%	1,2%
-1,6	53%	57%	57%	55%	56%	57%		0,0%	0,6%	0,7%	0,8%	0,9%	1,1%
-1,5	53%	55%	56%	55%	56%	58%		0,1%	0,4%	0,6%	0,6%	0,8%	1,3%
-1,4	53%	55%	56%	56%	57%	59%		0,2%	0,4%	0,7%	0,9%	1,4%	1,9%
-1,3	54%	55%	56%	56%	57%	59%		0,2%	0,4%	0,6%	0,8%	1,3%	1,8%
-1,2	54%	56%	57%	57%	58%	60%		0,2%	0,6%	0,7%	0,9%	1,4%	2,0%
-1,1	54%	56%	56%	56%	57%	60%		0,2%	0,5%	0,6%	0,8%	1,3%	1,9%
-1,0	54%	56%	56%	56%	58%	60%		0,2%	0,5%	0,7%	0,9%	1,4%	2,0%
-0,9	53%	55%	56%	57%	57%	59%		0,2%	0,4%	0,6%	0,8%	1,2%	1,9%
-0,8	54%	55%	56%	56%	57%	59%		0,2%	0,4%	0,6%	0,8%	1,0%	1,7%
-0,7	54%	55%	56%	57%	58%	59%		0,2%	0,4%	0,5%	0,7%	1,1%	1,9%
-0,6	54%	56%	57%	57%	58%	59%		0,2%	0,4%	0,6%	0,9%	1,3%	2,0%
-0,5	54%	56%	57%	57%	58%	60%		0,2%	0,4%	0,6%	0,9%	1,4%	2,1%
-0,4	54%	55%	56%	57%	58%	60%		0,2%	0,3%	0,5%	0,8%	1,3%	2,0%
-0,3	54%	55%	56%	57%	59%	60%		0,1%	0,4%	0,6%	0,8%	1,5%	2,1%
-0,2	54%	55%	56%	57%	59%	60%		0,1%	0,3%	0,5%	0,7%	1,5%	2,1%
-0,1	54%	55%	56%	56%	58%	60%		0,1%	0,3%	0,4%	0,6%	1,4%	1,9%
0,0	54%	55%	55%	56%	58%	59%		0,1%	0,3%	0,5%	0,6%	1,3%	2,0%
0,1	53%	54%	55%	56%	58%	59%		0,1%	0,2%	0,4%	0,6%	1,3%	2,0%
0,2	53%	54%	55%	56%	58%	60%		0,1%	0,1%	0,3%	0,6%	1,3%	2,1%
0,3	54%	54%	55%	56%	58%	60%		0,1%	0,2%	0,3%	0,6%	1,4%	2,2%
0,4	53%	54%	55%	56%	58%	60%		0,1%	0,2%	0,4%	0,6%	1,4%	2,3%
0,5	54%	54%	55%	56%	58%	60%		0,1%	0,2%	0,4%	0,6%	1,4%	2,2%
0,6	54%	56%	56%	57%	58%	60%		0,2%	0,3%	0,5%	0,7%	1,5%	2,3%
0,7	55%	55%	56%	56%	59%	60%		0,1%	0,2%	0,4%	0,7%	1,6%	2,5%
0,8	55%	56%	56%	56%	58%	60%		0,1%	0,2%	0,3%	0,7%	1,5%	2,4%
0,9	56%	56%	57%	57%	59%	61%		0,2%	0,4%	0,6%	0,8%	1,8%	2,8%
1,0	57%	57%	57%	56%	59%	61%		0,3%	0,5%	0,7%	0,9%	1,9%	2,9%
1,1	56%	57%	57%	57%	60%	61%		0,3%	0,5%	0,7%	1,0%	2,1%	3,0%
1,2	57%	58%	58%	58%	60%	61%		0,3%	0,6%	0,8%	1,1%	2,2%	3,2%
1,3	57%	58%	58%	58%	60%	62%		0,3%	0,6%	0,8%	1,2%	2,3%	3,5%
1,4	58%	59%	59%	59%	61%	62%		0,4%	0,7%	0,9%	1,3%	2,3%	3,6%
1,5	57%	59%	59%	59%	61%	63%		0,3%	0,7%	0,9%	1,3%	2,6%	3,7%
1,6	57%	59%	59%	59%	60%	63%		0,4%	0,8%	0,8%	1,2%	2,6%	3,5%
1,7	59%	60%	61%	61%	62%	65%		0,8%	0,8%	0,6%	1,3%	2,9%	4,6%
1,8	63%	59%	61%	57%	62%	67%		0,9%	0,7%	0,6%	1,2%	3,5%	5,6%

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Dr. Oliver Reiss, CFTe, MFTA, received a master's degree in physics from the University of Osnabruck (1998) and a Ph.D. in mathematics from the University of Kaiserslautern (2003)—the latter for his research on financial mathematics performed at the Weierstrass-Institute in Berlin. Since then, he has worked in the banking industry and today he is a self-employed consultant for financial institutions with a focus on risk controlling, derivatives pricing (quant), and related IT implementations by his company Tremti GmbH. Lately the software company TRC-Software has been founded to serve small banks for regulatory reporting and Treasury management.

After he quit his employment at a mid-size bank in 2011 to start his consultancy business, he also joined the International Federation of Technical Analysts (IFTA) via its German association VTAD and received subsequently the CFTe and MFTA certifications, and his MFTA thesis on the Empirical Mode Decomposition was rewarded by with the John Brooks Memorial Award in 2019. Since 2024 he serves as Secretary and Treasurer for IFTA.

Due to this mathematical and programming expertise, he is focused to combine the classical knowledge of Technical Analysis with rigorous statistics, institutional risk management and more sophisticated algorithms. His focus is mostly concentrated on trend-following strategies over mid-term time horizons. His latest research paper "Trend – Emotion – Timing" establishes a new way to chart the market of stocks. It combines trend following ideas based on a large statistical evidence with classical portfolio optimization and is rewarded by the Founders Award of the National Association of Active Investment Managers (NAAIM).

NAAIM NATIONAL ASSOCIATION OF ACTIVE INVESTMENT MANAGERS

The Intelligent Fund Investor

By Joe Wiggins

Reviewed by Regina Meani CFTe, MSTA, AMT

In his conclusion, Joe Wiggins asks the question: *What does it take to be an intelligent fund investor?*[i] There is part of his answer in every chapter. Wiggins believes that the answer lies in not having expertise in any form of analysis of the markets or a *sophisticated understanding of how global economies function*[ii] but rather our ability to harness our own behaviour.

Wiggins suggests that there are three main obstacles to forming good decisions when considering where to invest. Number one portrays the wealth of funds inhabiting the markets giving us too much choice. Number two suggests fund investing is too difficult. To avoid the difficulty Wiggins introduces the idea that we instinctively opt for the funds showing a strong past performance and a history of good returns. Along with this we also favour "star" performing fund managers. These choices can be problematic and prove damaging to our profits. Not to chase the "stars" becomes a recurrent message as we continue to read. Number three states that there is too much noise. The noise includes the short-term market fluctuations, the flood of information surrounding the global markets and economies and the stories that people like to tell within this arena. The three points should not affect our investment decisions but unless we can control our behaviour we find ourselves *easily tempted into injudicious and unnecessary activity*[iii].

Each chapter of the book seeks to unravel some of the problems we face when we enter the fund investment world. Paramount is our ability to recognize how we handle the information presented to us and how we can use it to our advantage. Through the chapters Wiggins highlights the pros and cons of investing with star performers or choosing a simple investment fund over a complex one. Should we listen to stories? Generally, everyone loves a good story but should we back it with our money?

Then should we invest in concentrated or diversified funds. Diversification makes sense but is it riskier? Is the fund manager incentivized in an appropriate way? *Never, ever, think about something else when you should be thinking about the power of incentives*-Charlie Munger[iv]

Wiggins poses an interesting hypothetical question in Chapter Nine: When should we fire Warren Buffet? Buffet is widely regarded as the best investor in history. If we are basing our investment choices on performance alone then we would most certainly have fired him. Why? Because most of us lack patience and if a fund under performs for a period, then most of us would sell out. Buffet's strategy selects high quality stocks that he intends to hold forever, but has the wisdom and behavioural control to quickly reverse an investment mistake. He has been credited with saying: *We agree with Mae West: "Too much of a good thing can be wonderful."* In this segment we are encouraged to know our investment horizons because time and timing are essential in our investment decisions.

Each chapter is followed by a ten-point summary as a check list before we move forward. This ensures that the book can be an excellent primer for the novice and a useful handbook for the more experienced investor.

Wiggins concludes that Intelligent fund investors must understand themselves better than they understand markets. A strong message carried through the book.

Notes

[i] Wiggins,J, The Intelligent Fund Investor, Harriman House Ltd, Hampshire, Great Britain, 2022. Pg 207

[ii] Ibid.

[iii] Ibid., p 5-6

[iv] Ibid., p 153

[v] Ibid., p 207

Author Profiles

Seiji Adachi, CMTA, CFTe, MFTA

Seiji Adachi has worked as an economist at Daiwa Securities, Deutsche Securities, Marusan Securities, and others. He also holds an MBA from Hitotsubashi University, Graduate School of International Corporate Strategy, and is interested in how economic indicators and other information are incorporated into stock prices, which led him to technical analysis through research and reflection. His current interest is how to integrate macroeconomic analysis and technical analysis to forecast stock prices. He is currently planning an online salon to provide investment information.

Mohamed Ashraf, MFTA, CFTe, CETA

Mohamed Ashraf is the Technical Analysis Director for CI-Capital, the premier investment bank in Egypt with market-leading leasing, microfinance, investment banking, securities brokerage, asset management and research franchises. CI-Capital is totally owned by Bank Misr. Prior to this he was the Head of the Technical Analysis for Dynamic Securities Brokerage Company—CI-Capital member.

Mohamed served as a board member and vice president for the Middle East and Africa region in the International Federation of Technical Analysts (IFTA) from 2010 until 2016. During this period, he implemented an MOU agreement between IFTA and the United Arab Emirates Securities and Commodities Authority (ESCA), an MOU agreement between IFTA and the Capital Market Authority in Sultanate Oman (CMA), and he was responsible for translating the CFTe bank of questions into Arabic language—along with the responsibility of correcting the Arabic exams. He also served as a board member in the Egyptian Society of Technical Analysts (ESTA) from 2011 until 2015, and he is a key education committee member in (ESTA) since 2007.

Mohamed has taught technical analysis at many financial institutions and universities for more than 18 years; most notable were the annual Egyptian Stock Market Conference in the international conference center hall, The Egyptian Financial Supervisory Authority in Cairo, the central bank of Egypt (CBE), the Arab Federation of Exchanges (AFE), the Securities and Commodities Authority ESCA in its headquarters in Dubai, Emirates Institute for Banking and Financial Studies (EIBFS), the Capital Market Authority in Sultanate of Oman, Capital Markets Authority of State of Kuwait, courses held along with Union of Arab Securities Authorities (UASA), the Omani Securities Association, the American University in Cairo, the German University in Cairo (GUC), the annual portfolio management course held in the Egyptian Association of the Investment Management, courses held along with Thomson Reuters in Egypt for their special clients, courses held along with Kaplan Professional Middle East, online webinars with Swissquote bank, the Faculty of Economics and Political Sciences, the Faculty of Commerce in Cairo, Ein Shams Universities and Nile University.

Mohamed graduated from the Economics & Political Sciences department at Cairo University. He is a Certified ESTA Technical Analyst (CETA), a Certified Financial Technician (CFTe), and holds a Master's degree in Financial Technical Analysis (MFTA) from the International Federation of Technical Analysts IFTA.

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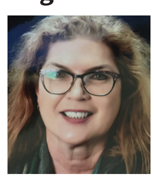
Alessandro Greppi, Ph.D., MFTA

Alessandro Greppi earned his Ph.D. in Economics and Technology Management from the University of Pavia, focusing his research on the use of artificial intelligence in stock markets. Since 2017, he has been a portfolio manager at Zurich Investments Life, where he concentrates on developing tactical asset allocation models, AI-based models for selecting ETFs and mutual funds, ESG products, and technical analysis of cross-assets.

He is also a board member of SIAT (Italian Society of Technical Analysis) and IFTA (International Federation of Technical Analysts). Since 2019, he has been a lecturer in the master's program in Financial Market Technical Analysis organized by SIAT, teaching financial statistics, machine learning, big data, portfolio analysis, and sentiment analysis of social networks. He also coordinates a data science course dedicated to institutional investors.

Regina Meani, CFTe, MSTA, AMT



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

Davide Pandini, Ph.D., CMT, MFTA, CFTe, CSTA

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.

In the field of technical analysis, Dr. Pandini is a Certified Financial Technician (CFTe) and a Master of Financial Technical Analysis (MFTA) of IFTA, holds the Chartered Market Technician (CMT) designation from the CMT Association, and is a professional member of SIAT (Società' Italiana Analisi Tecnica). In 2021, he was the recipient of the XII SIAT Technical Analyst Award in the Open category. He was a speaker at SIAT Trading Campus in 2022, in Milano, Italy, and at the Investing and Trading Forum in 2022 and 2023, in Rimini, Italy. He was the winner of the prestigious IFTA 2021 John Brooks Memorial Award and was a speaker at the IFTA 2023 annual conference in Jakarta, Indonesia, at Bogu Investment Forum 2024, in China, and will be at the IFTA 2024 annual conference in Boao, Hainan, China.

Davide served as volunteer at the Universal Exhibition Expo2015—*Feeding the Planet, Energy for Life*—in Milano, Italy.

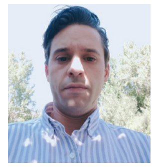
Oliver Reiss, Ph.D., MFTA, CFTe

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

As a private investor, Oliver is interested in technical analysis and due to his mathematical and programming expertise, he is now focused on the developing and back-testing of mid-term trading strategies based on more sophisticated algorithms. He joined the VTAD in 2011 when he became a freelancer and currently serves as deputy manager of the VTAD's regional group in Dusseldorf.

Oliver received his MFTA for his thesis on the application of the Empirical Mode Decomposition to technical analysis, which was rewarded with the John Brooks Memorial Award in 2019. As a frequent attendee of IFTA conferences, he also presented the results of his MFTA research at the IFTA Conference in Cairo.

Raúl Gómez Sánchez



Raúl Gómez is a researcher who has been publishing articles related to the stock market for more than five years, publishing them in the famous trading magazine in Spain and Latin America, Hispatrading Magazine. He has published more than 20 articles, most of them related to opening gaps, and aims to show a new perspective on them, demonstrating how they have the ability to detect short- and long-term market lows and highs. Currently, this author has positioned himself as one of the best researchers in the SSRN academic dissemination network, managing different accounts funded with strategies based on opening gaps, and publishing his technical indicators on the prestigious Trading View platform for public access.

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