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"I am always ready to learn although I do not always like being taught."

—Winston Churchill

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Letter From the Editor

By Dr. Rolf Wetzer, CFTe, MFTA

Dear IFTA Colleagues and Friends:

I hope that you, your family, and your friends came through the year healthy and safe. We are still living through strange times. Something unprecedented keeps us from doing what we are used to doing. Our world is divided into those who are vaccinated, and thus protected, and others who are potentially at risk. In some places, life is back to normal. In others, we still shelter by staying at home, wearing masks, and restricting ourselves from meeting with others. Unfortunately, this also applies to IFTA. For the second time in our history, there will be no in-person conference this year. Again, we have canceled Philadelphia and replaced it with an online conference. Instead of discussing Elliott, we count Corona waves nowadays. Definitely nothing we should get used to!

But despite the virus and the epidemic, there will be an *IFTA Journal.* Not business as usual, but nevertheless as normal as possible. IFTA is international and so is this *Journal.* Again, we have gathered articles from colleagues around the world.

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

We also have one paper that NAAIM has kindly made available to us. It is the winning paper of the Wagner Award. Again, we are more than happy about the long-lasting cooperation with NAAIM. I want to thank NAAIM for their support and especially Susan Truesdale for her kind cooperation.

I hope that you, your family, and your friends came through the year healthy and safe.

We also have two articles from colleagues from Germany and Spain. Both authors were speakers at an IFTA conference in the past. They share the same passion for using quantitative elements in their market analysis.

As reported in the last issue of the *IFTA Update,* J. Welles Wilder Jr. passed away this spring. He pioneered the use of indicators and data-driven analysis in the 1970s. IFTA recognized him at last year's conference for his life's work. We pay tribute to J. Welles Wilder Jr. here through memories of his colleagues and present a selection of his ideas.

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

Finally, I need to thank Aurélia Gerber for her help and especially Linda Bernetich. Without Linda and her team this *Journal* wouldn't exist. It's as simple as that. Thanks for your patience and organizational skills.

I hope that you will like the *Journal.*

Best regards,
Dr. Rolf Wetzer, CFTe, MFTA

IFTA Journal

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Observation of Yield Points of Trends

By Shinji Okada, CMTA, CFTe, MFTA

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Abstract

How long will the trend last? I've been pursuing this question ever since I encountered the financial market. If you could detect the end point of trends in the stock, bond, exchange, commodity, and other financial markets, you would be able to avoid following the trend near the end point. Also, if you have detected the end point of the trend, that means you have detected the starting point of the next trend. I have been exploring how to use "regression trends," one of the methods of trend analysis, to solve this question. Since I could not find any literature that provides practical explanation on a method to use regression trends, I decided to create one through this thesis. I found literature that says prices keep going up and down and definitely do not continue following the regression. That's true, but there was a discovery there. Thinking that prices are bound to depart from the regression at some time or other, I studied the importance of regression analysis of trends and sought a way to find the end point of a trend. In this thesis, I will describe the method and its possibilities so that readers can use it to avoid following the trend at the ceiling or bottom of a trend. In this thesis, I named the point at which a trend closes its short life the "yield point of the trend," inspired by the stress-strain curve.

In this study, I developed an index named the standard error enhanced index to measure the yield point of a trend and used it for analysis. As a result of observation using the Nikkei stock average index, it became easier to observe the yield point of a trend and I could confirm the movement of a trend to its end. On the other hand, different observations were obtained in AUD/USD and other markets. I will continue study for verification. I hope that this study will contribute to the development of financial markets in the 21st century and help market participants make better decisions.

Introduction

How long will the trend last? I've been pursuing this question ever since I encountered the financial market. In the approximately seven years I spent as a securities broker, I saw many investors buying at the ceiling of an uptrend and selling at the bottom of a downtrend. If you trade in line with the trend near the end of the trend, your investment assets will be hurt badly. You need to detect the end point of the trend. Since the time I was a securities broker, I have wanted to help investors in one way or another. Also, if you have detected the end point of the trend, that means you have detected the starting point of the next trend. I think it is not too late to trade in line with the trend after confirming the turnaround of the trend.

To analyze trends, I started with drawing trend lines and channel lines as a means to grasp the trend. Drawing trend lines and channel lines seemed to make the trend clearer than in a price-only chart. However, since trend lines and channel lines are drawn according to the drawer's subjectivity, regularity cannot be found.

Therefore, I chose regression trends as a method to grasp the trend which has already occurred. I thought arbitrariness of the drawer could be eliminated by using regression trends, or regression analysis of price and elapsed time. However, when I researched examples and explanations of the use of regression trends, all I could find was something like "Enter an arbitrary time axis and trade against the trend with a standard error of ±2σ." I generally agree, but I want to use it in a more specific way. As there is no literature available that explains the practical use of regression trends, I decided to create one in this thesis. One literature says that it is impossible that financial markets, which keep going up and down, continue following the regression. That's true, but there was my discovery. I only need to measure the point of breaking away.

I think that a trend is a series of "phenomena." It's impossible that a trend is driven by only one factor. Price movements continue to be affected by market participants' decisions and buy/sell orders for the commodity. As time passes from the occurrence of the trend, starting from preceding price movements, rumors are generated, factors are announced, analysts publish reports, specialized magazines cover it, the media spotlight it, and amateur investors participate by trading in line with the trend. Then the trend comes to an end. In this way, trends are affected by a variety of factors. The regression trend approach enables analysis of a trend, a phenomenon, from price and elapsed time. I attach importance to comprehensive analysis of the trend as a whole, a phenomenon that incorporates detailed analysis and even noise. If you have studied the Elliott wave, the Ichimoku Kinko Hyo, cycle analysis, etc., it will be easy to understand that time has a strong impact on the market. And by analyzing a trend by price and time, you can understand the current status of the trend.

I named the point at which a trend closes its short life the "yield point of the trend," inspired by the stress-strain curve. I created all the following charts in Excel from data provided by QUICK Corp.

The Factors and the Method

First, I will explain a practical way to use regression trends. Regression trends are used to understand whether the present trend is continuing or has already turned around. I will explain below in an example of an uptrend. Closing prices are used in all the analyses in this thesis.

The starting point of a regression trend is the low price before the previous high was overtaken. In Figure 1, this is C. You may want to draw the line from A, but there is a downtrend from B to C, so A is not suitable for the starting point of the latest trend. And the latest trend is assumed to be an uptrend because the previous high of B was overtaken at D. Therefore, C is the starting point of the trend.

Figure 1. Nikkei225 (2012/10/01–2012/11/30)

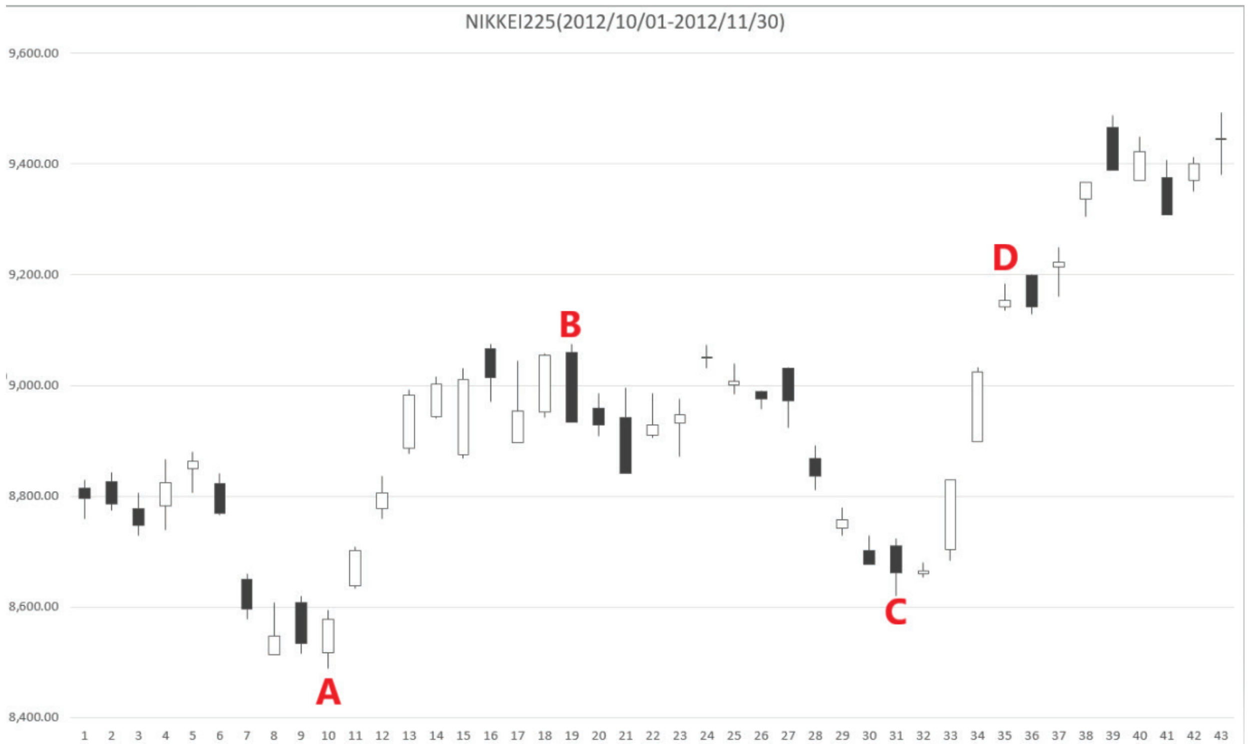
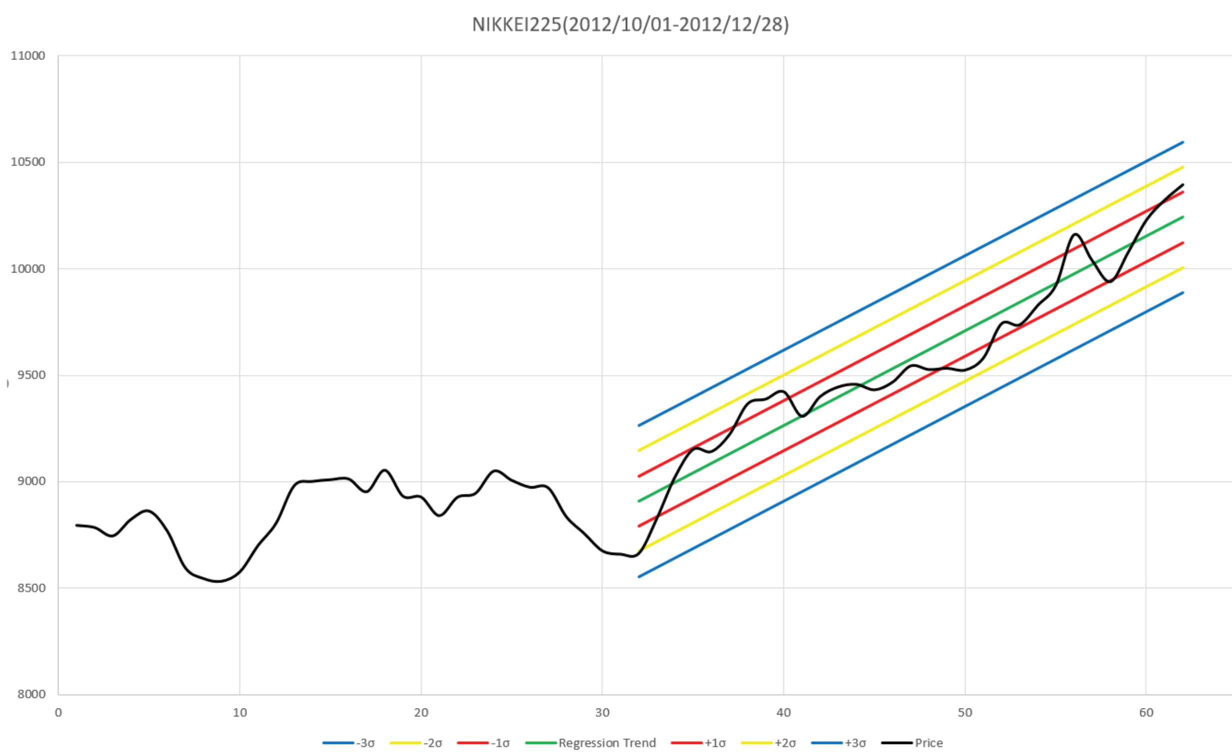


Figure 2 shows a regression trend line drawn from C of Figure 1.

Figure 2. Nikkei225 (2012/10/01–2012/12/28)



The black line in Figure 2 indicates the closing price (¥10395.18), and the green line represents the regression trend (¥10241.85). The red line indicates the value of the standard error ±1σ (¥10359.94, ¥10123.75), the yellow line ±2σ (¥10478.04, ¥10005.66), and the blue line ±3σ (¥10596.14, ¥9887.56). Setting November 13, 2012, as Day 1, I calculated the regression trend backward from December 28, or Day 32 (regression analysis by closing prices of the 32 days and the elapsed time of 32 days). The standard error is ¥118.0962.

Next, I will explain the standard error. By using the standard error in the analysis, the accuracy of the trend estimation can be measured. A sharp increase in the standard error during the measurement of a trend means that the estimation accuracy is decreasing, which suggests that the perception of the trend during the measurement is incorrect. "Standard error +1σ" means the value of the regression trend plus the value of the standard error, and "-1σ" means the value of the regression trend minus the standard error. Similarly, "Standard error +2σ" is the value of the regression trend plus two times the standard error, and "-2σ" is the value of the regression trend minus twice the standard error. "+3σ" is the value of the regression trend plus three times the standard error, and "-3σ" is the value of the regression trend minus three times the standard error. It is expected that about 68% of the prices that continue to rise or fall along the trend will be within the range of ±1σ above and below the regression trend, and about 27% will be within the range of ±2σ, totaling about 95%.

Let us confirm about a trend itself. An uptrend means that the price continues to rise from the starting point of the trend, whereas a downtrend means that the price continues to fall from the starting point of the trend. If the price is falling and making the standard error continue to expand beyond the value of standard error -2σ, we can infer a downward trend. Even if the price is making the standard error continue to expand beyond -2σ, it is not a downtrend if the price is rising.

The key point to confirming if an uptrend has turned into a downtrend is whether the standard error of the regression trend being measured has expanded while the price has been falling. When the price has been falling and the standard error has been expanding, it is assumed that a downtrend started from the previous high price. As long as the price continues to fall without recovering to the previous high, the downtrend is recognized. If the standard error continues expanding as the price falls while an uptrend is being measured, it is determined that a downtrend started from the previous high price. However, it may be a minor decline during an uptrend, and the price may resume its rise. Also, the standard error becomes larger as the upward and downward price movements increase with the lapse of time. Therefore, it is necessary to check if the trend continues or not by checking whether the standard error is expanding rapidly or not.

The progress of expansion of the standard error cannot be grasped from a chart simply indicating the price, regression trend, and standard error. Therefore, I created the "standard error enhanced index" to check changes in the standard error in a trend.

Standard error enhanced index = Number of days elapsed × Change in closing price from previous day (%) × Change in standard error from previous day

In the case of daily time axis, this index is explained as follows.

- Number of days elapsed: Set the starting point of the trend as Day 1. If 14 business days have elapsed, it's Day 14. The purpose is to reflect the effect of the time elapsed since the occurrence of the trend.
- Change in closing price from previous day (%): The percent change in the closing price of the day from the previous day. If the closing price is 2.1% lower than the previous day, the value is -2.1. The purpose is to reflect the volatility of the price.
- Change in standard error from previous day: The change in the standard error calculated from the starting point of the trend to the latest closing price, expressed in the change from the previous day. If the standard error of the day is 95 and that of the previous day is 15, the value is 80. The purpose is to reflect the extent to which the standard error is affected by price movements.

In this formula, the longer the trend continues, the higher the standard error enhanced index tends to rise. I think it is no problem. The longer the trend continues, the more market players recognize it and participate in it, which naturally leads to higher volatility. To reflect this, the number of days elapsed is also updated daily in the calculation of the index.

If the value is negative, it is converted to an absolute value. In order to enhance reproducibility, I used standard error values obtained by regression analysis of the number of days elapsed and the closing price entered in the Excel data analysis tool.

Results

In this section, I will explain using examples of the Nikkei stock average.

Figure 3. Nikkei225 (2012/11/13—2013/01/04)

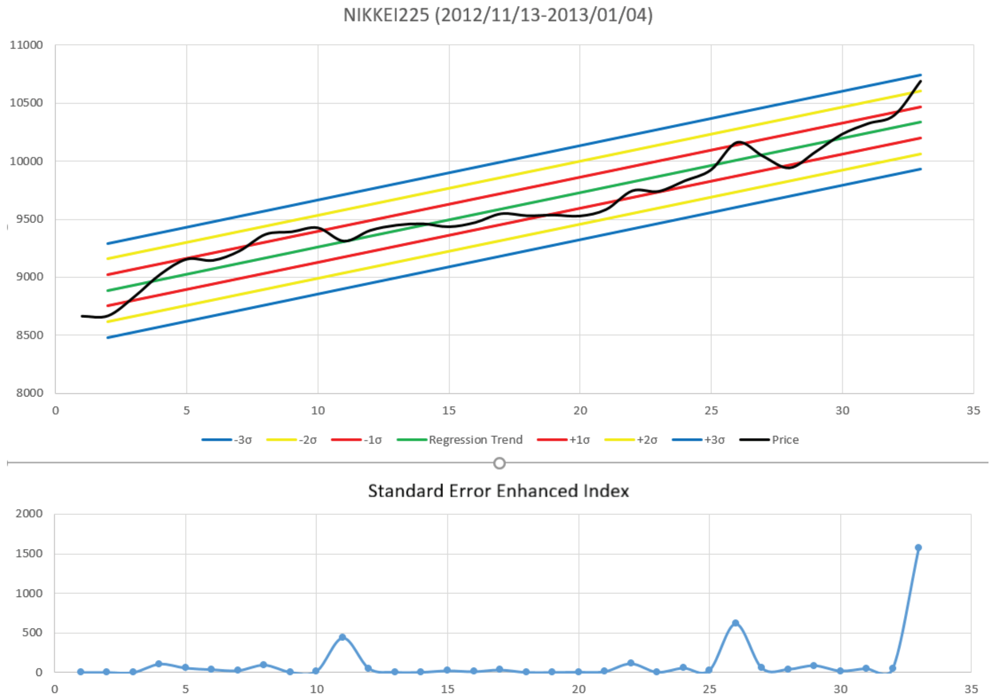
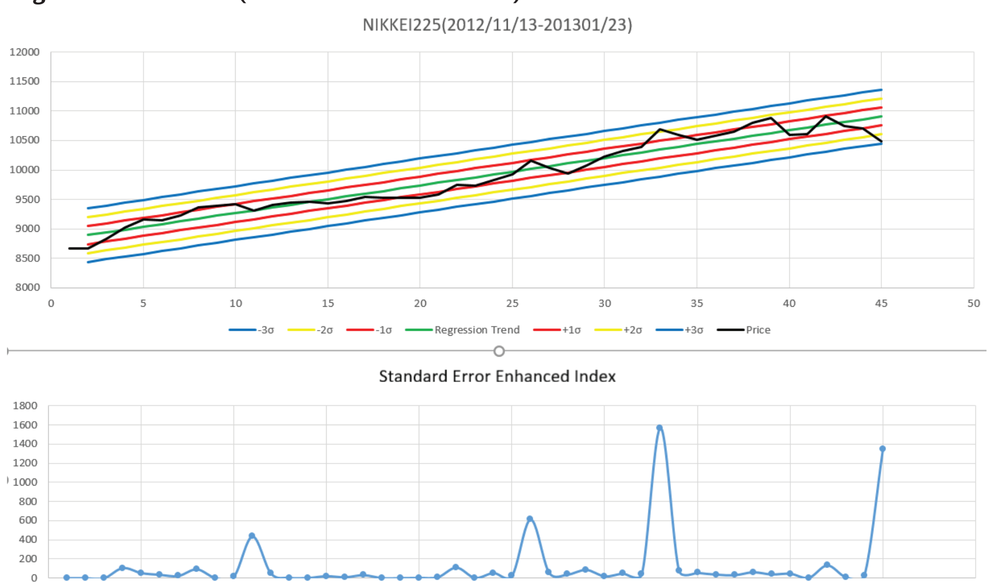


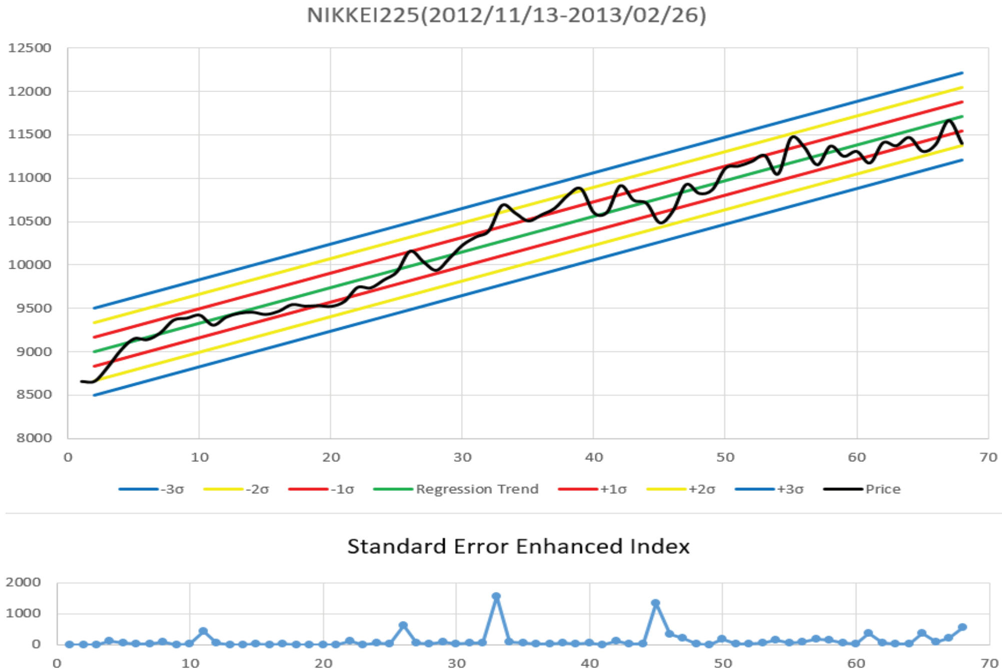
Figure 3 shows measurement of the Nikkei stock average following Figures 1 and 2, in which the closing price of 2012/11/13 is the starting point of the trend. The lower part of Figure 3 shows the standard error enhanced index of January 4, 2013, which is 1570.98 points (33 days elapsed, closing price up +2.818% from the previous day, and standard error up +16.89 from the previous day: 33 × 2.818 × 16.89 = 1570.98). This is the first yield point. If the price drops to the green regression trend in the middle, the yield point is considered to have worked. If this yield point is passed, the trend is considered to have shifted from the elastic region to the plastic region. It's time to refrain from placing new buy orders. In this case, the price moved toward the regression trend, so it is considered that the trend from November 13 was continuing.

Figure 4. Nikkei225 (2012/11/13—2013/01/23)



In Figure 4, the standard error enhanced index is 1350.517. The closing price has also dropped below -2σ, so it is considered that the yield point has been reached. If the closing price continues to fall after Day 46, the downtrend from the previous high is considered to be continuing. If the uptrend resumes without turning into a downtrend, it is considered that the minor trend from January 4 was contained in the uptrend since November 13.

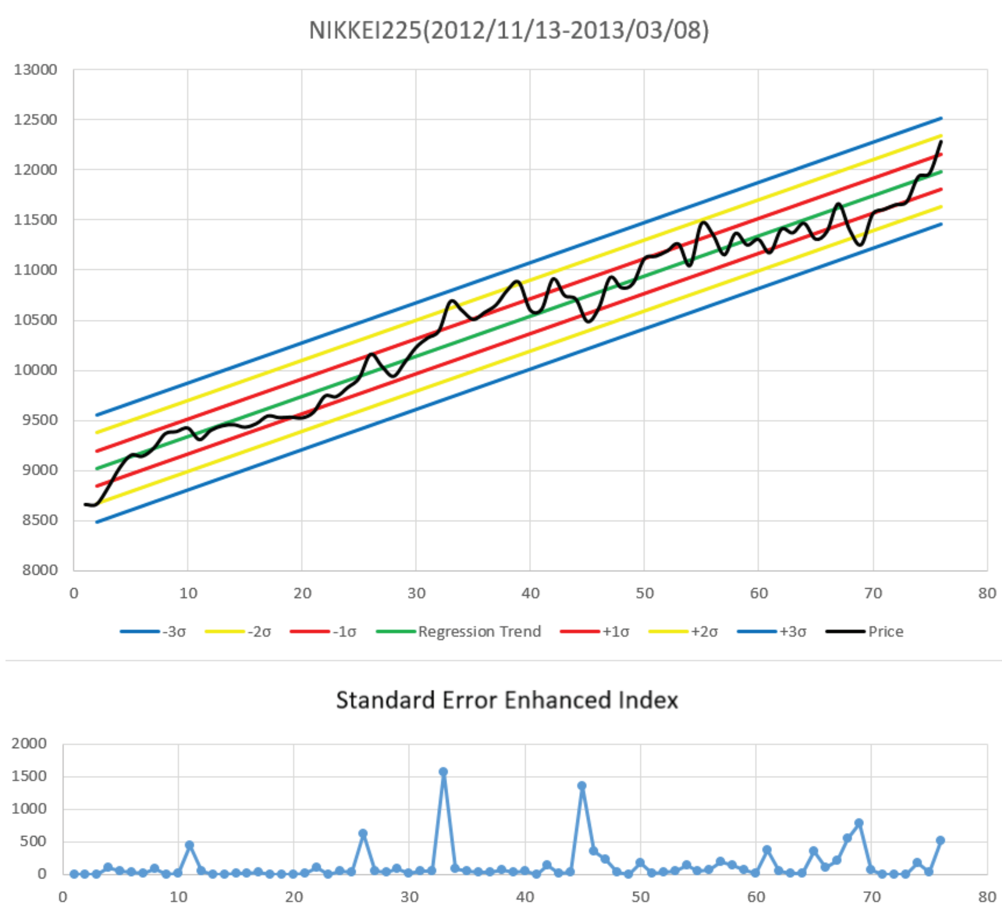
Figure 5. Nikkei225 (2012/11/13—2013/02/26)



In Figure 5, the standard error enhanced index has exceeded the previous high and the closing price has dropped below -2σ, so it is considered to be a yield point. If, after Day 69, the standard error enhanced index exceeds the previous high while the closing price declines, the market is considered to have passed the yield point and shifted to a downtrend.

In Figure 6, the standard error enhanced index has exceeded the previous high, but the closing price has not exceeded +2σ, so it is not a yield point.

Figure 6. Nikkei225 (2012/11/13—2013/03/08)



In Figure 7, a yield point is observed. The standard error enhanced index has exceeded the previous high, and the closing price has fallen below -2σ. If the closing price continues to fall and the standard error enhanced index continues to hit new highs, it means the trend has passed the yield point.

Figure 7. Nikkei225 (2012/11/13–2013/04/01)

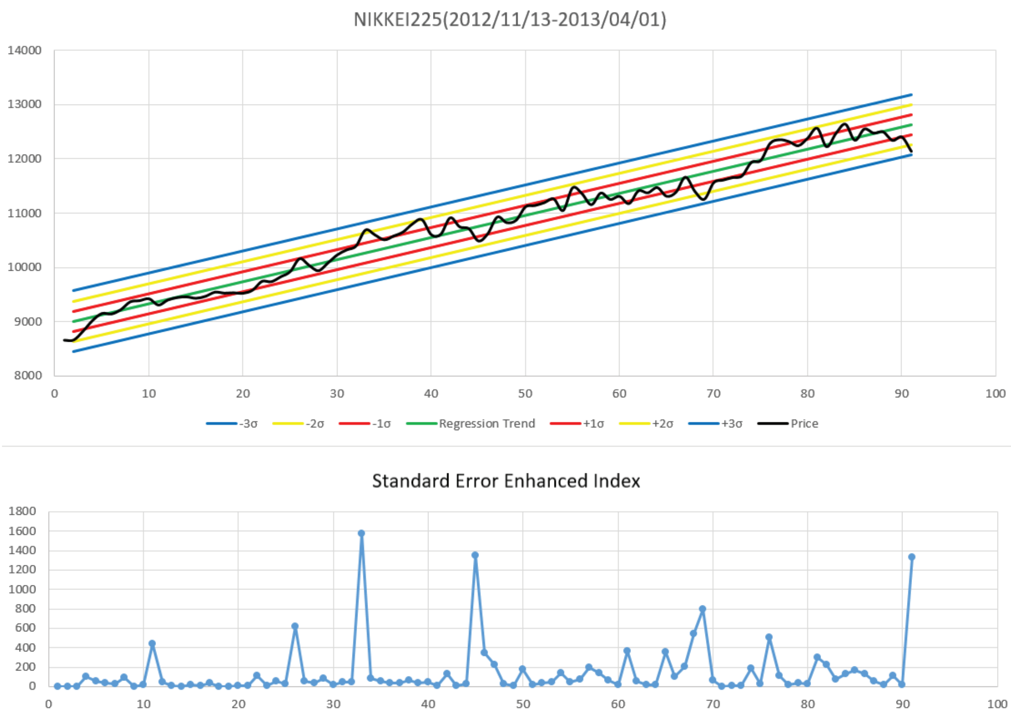
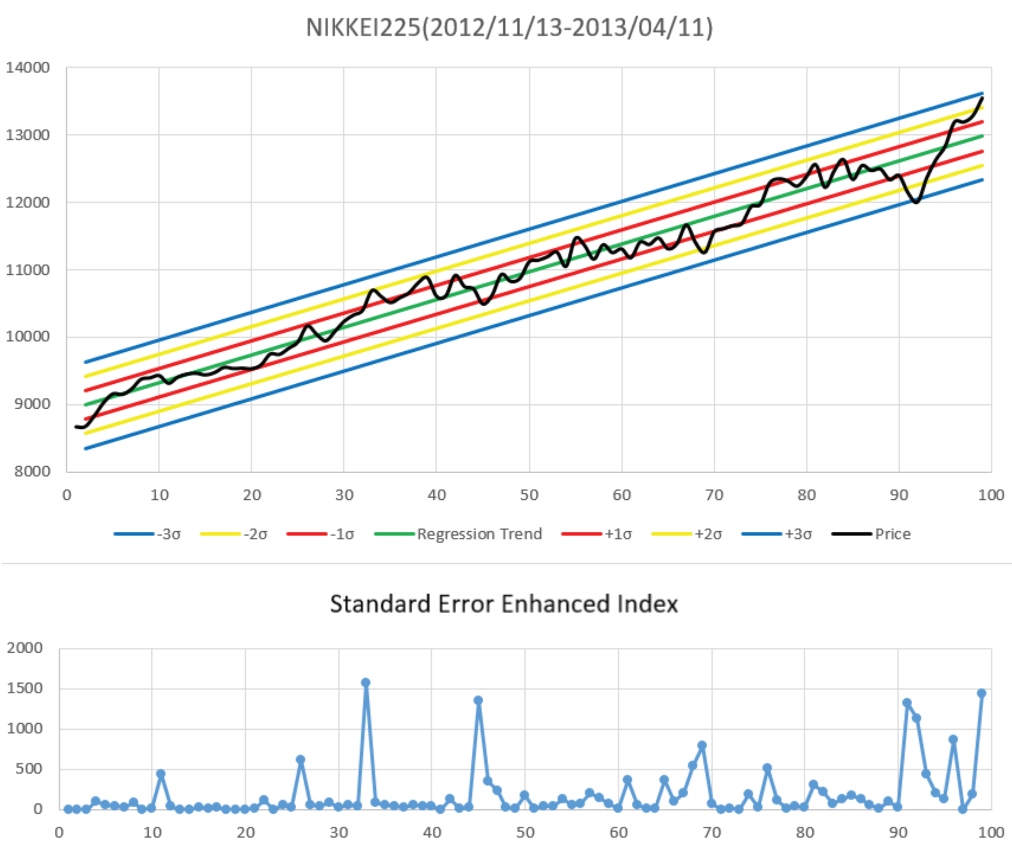


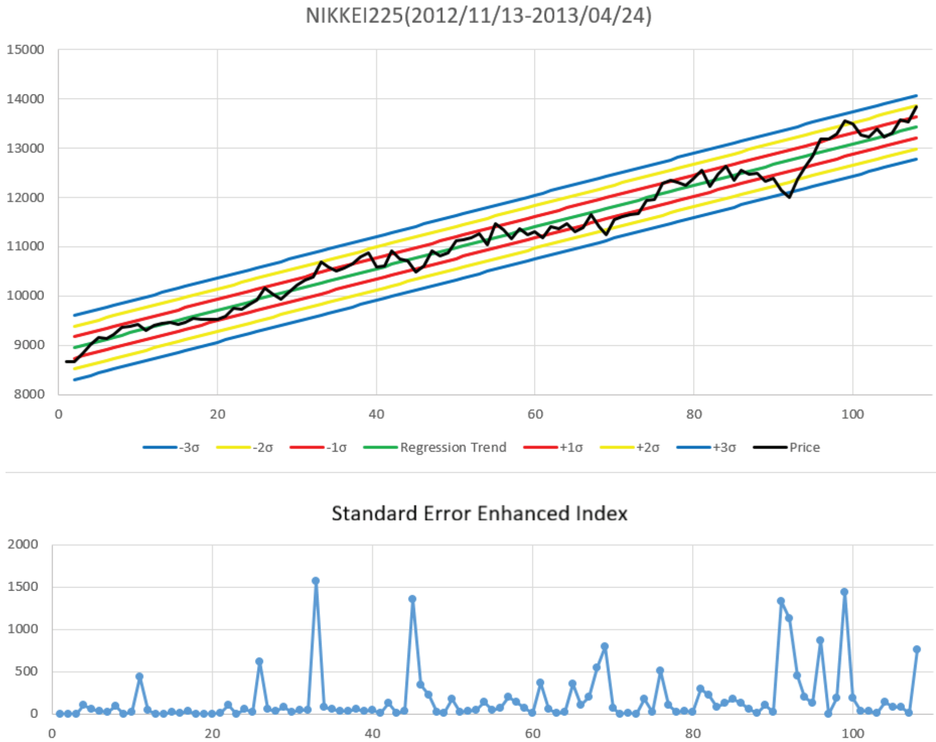
Figure 8. Nikkei225 (2012/11/13–2013/04/11)



In Figure 8, a yield point is observed in the latest standard error enhanced index.

In Figure 9, too, a yield point is observed in the latest standard error enhanced index.

Figure 9. Nikkei225 (2012/11/13–2013/04/24)



In Figure 10, too, a yield point is observed in the latest standard error enhanced index.

Figure 10. Nikkei225 (2012/11/13–2013/05/07)

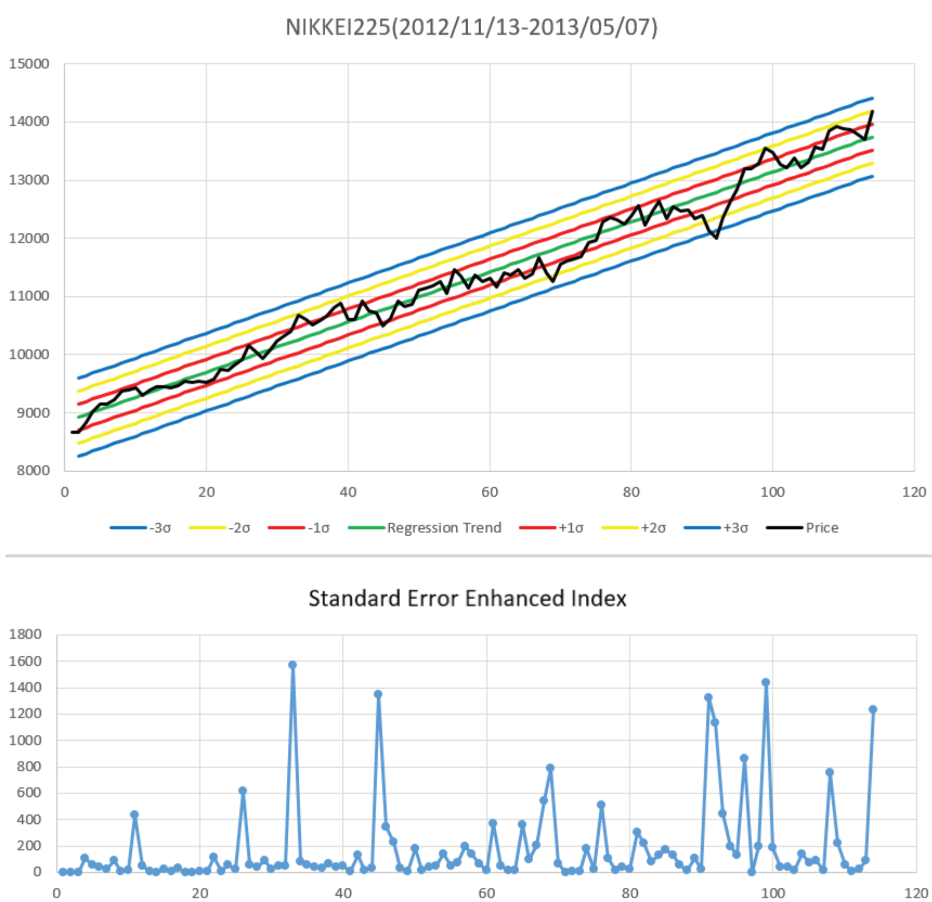
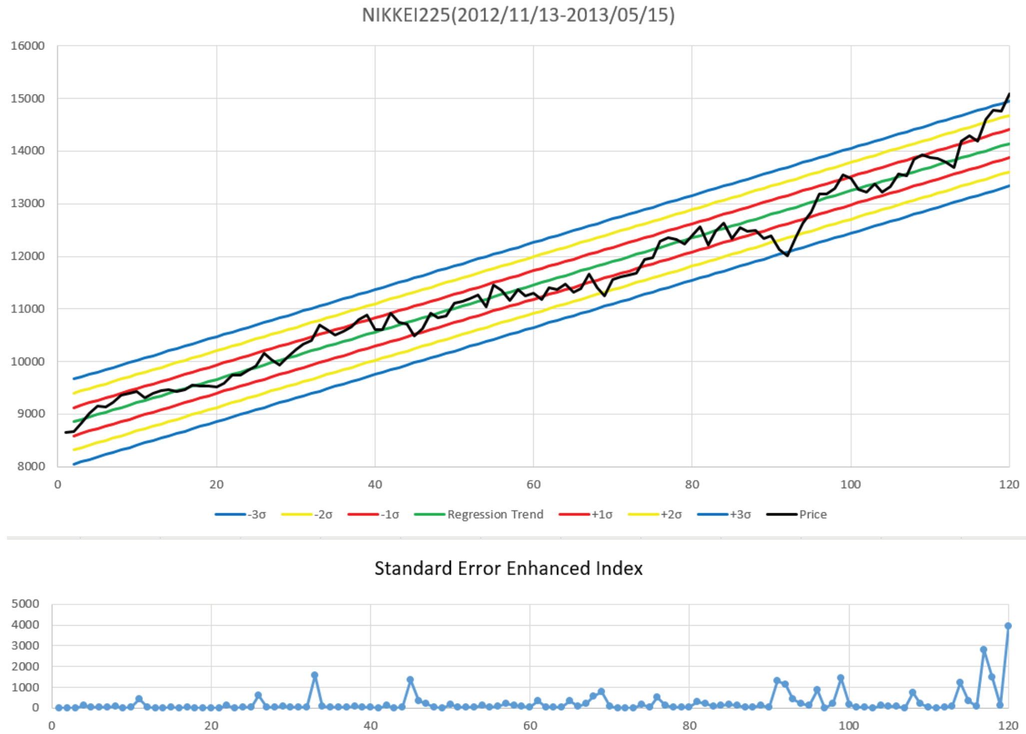


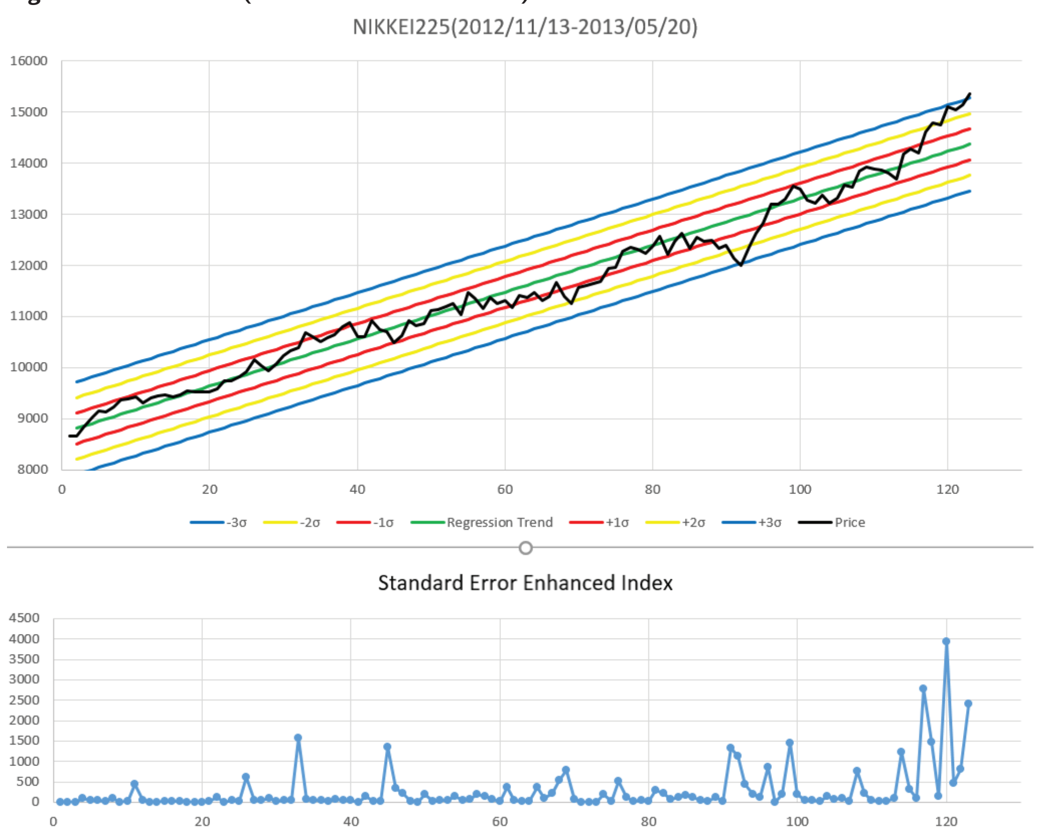
Figure 11. Nikkei225 (2012/11/13–2013/05/15)



After the yield point was observed in Figure 10, the closing price does not return to the regression trend and the standard error enhanced index hits a new high. Therefore, it is considered that the trend has broken through the yield point and shifted from the elastic region to the plastic region. The closing price does not fall immediately after the yield point is passed. The trend continues until the maximum stress is reached, so the uptrend is thought to be continuing as long as the price continues to hit new highs.

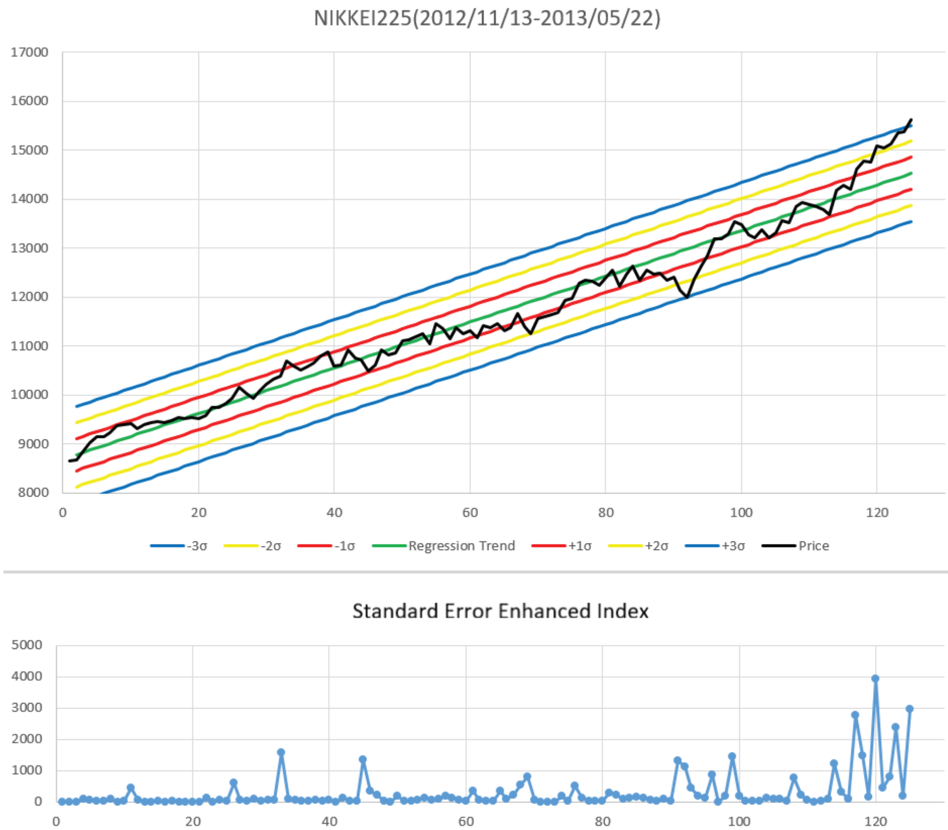
When a new high of the standard error enhanced index is no longer observed, it is considered that the maximum stress point has been passed, suggesting that a downtrend is approaching.

Figure 12. Nikkei225 (2012/11/13–2013/05/20)



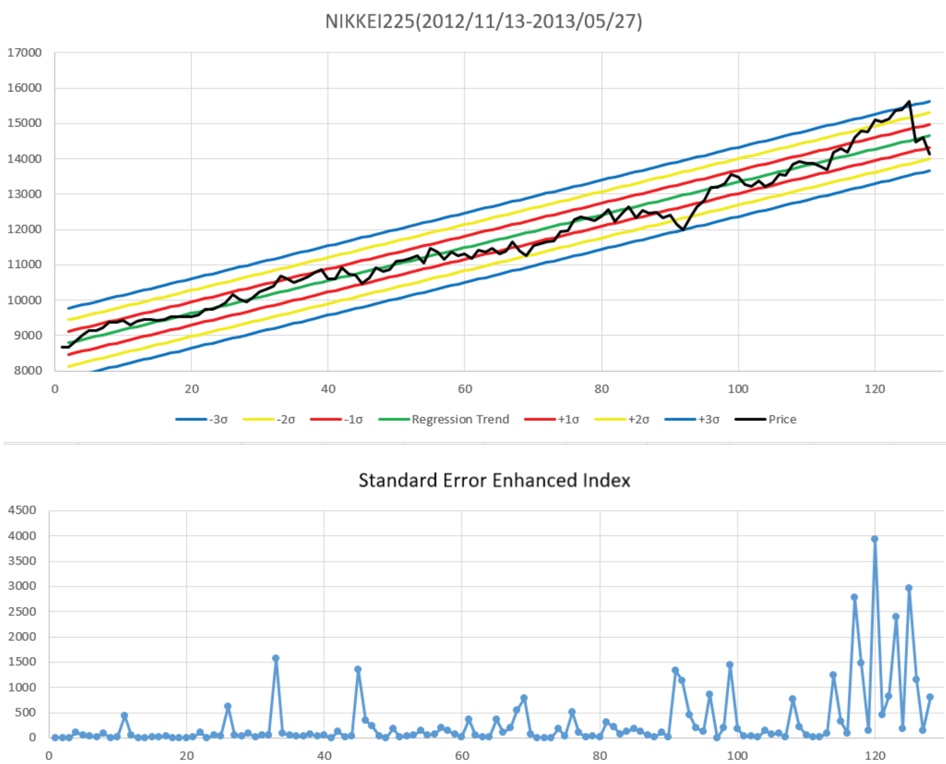
In Figure 13, the rise of the closing price is continuing, so the uptrend is maintained.

Figure 13. Nikkei225 (2012/11/13—2013/05/22)



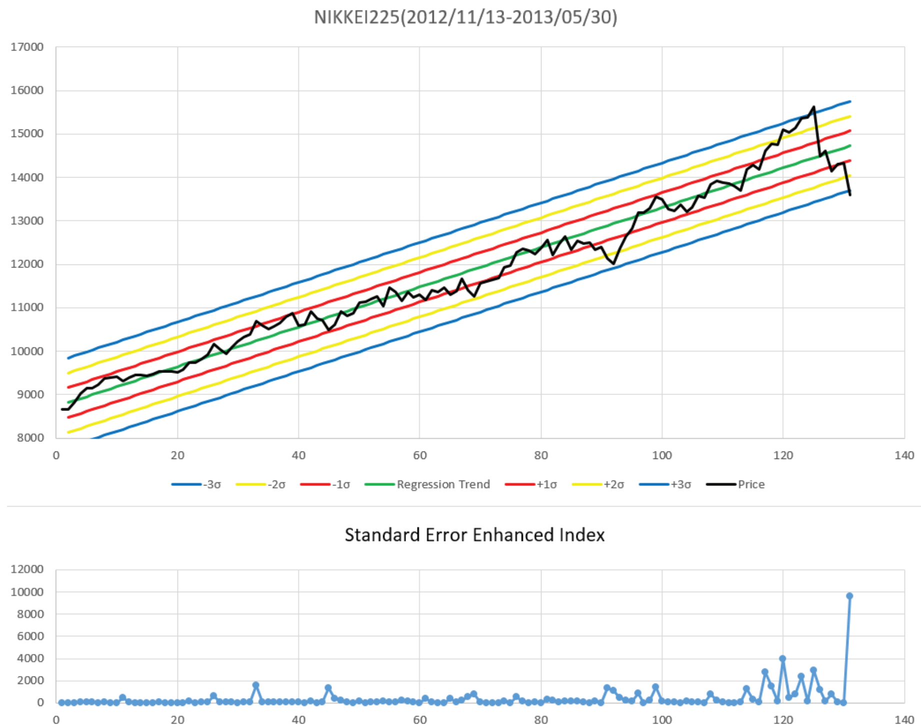
In Figure 14, although a decline of the closing price is observed, it is considered within the range of the trend unless the standard error enhanced index reaches a new high.

Figure 14. Nikkei225 (2012/11/13—2013/05/27)



In Figure 15, the closing price has fallen below -2σ and the standard error enhanced index has reached a new high. Therefore, it is considered that the trend that was continuing since November 13 has ended. Deciding that a new trend started on May 22, a market player should shift to measurement of a downtrend. It is not known whether it is a level trend or a downtrend.

Figure 15. Nikkei225 (2012/11/13—2013/05/30)

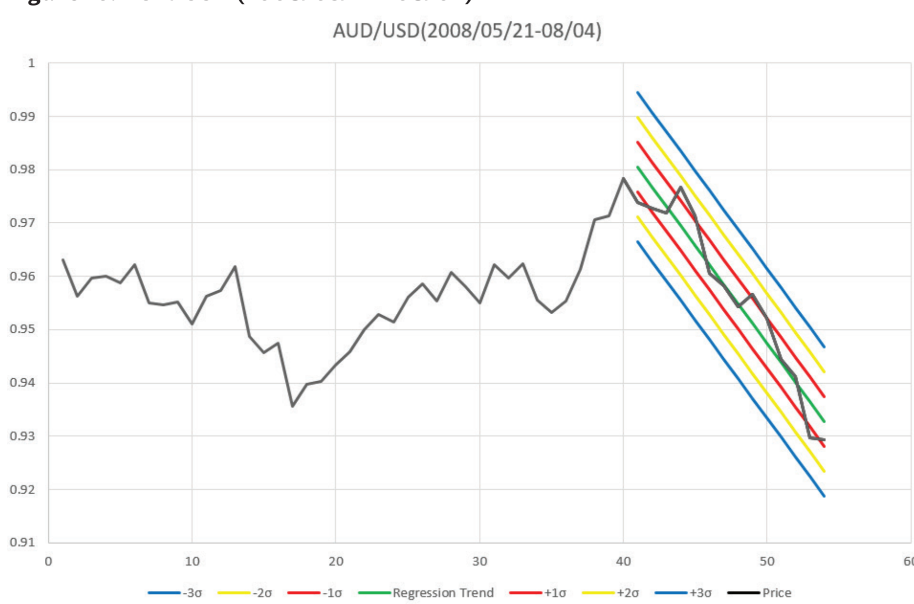


The first thing that can be confirmed from the above charts is that in a chart of the standard error and the price, the positional relationship is updated later with the lapse of time, and as a result, a closing price that was within ±2σ is frequently indicated outside the range of ±2σ as time passes. Such a phenomenon affects a decision solely based on the regression trend. But it has been found that using the standard error enhanced index along with the chart, the yield point can be checked to determine whether the trend will continue.

However, not all cases are as simple as the Nikkei stock average. As an example of this method not working well, I will now present analysis of AUD/USD daily charts.

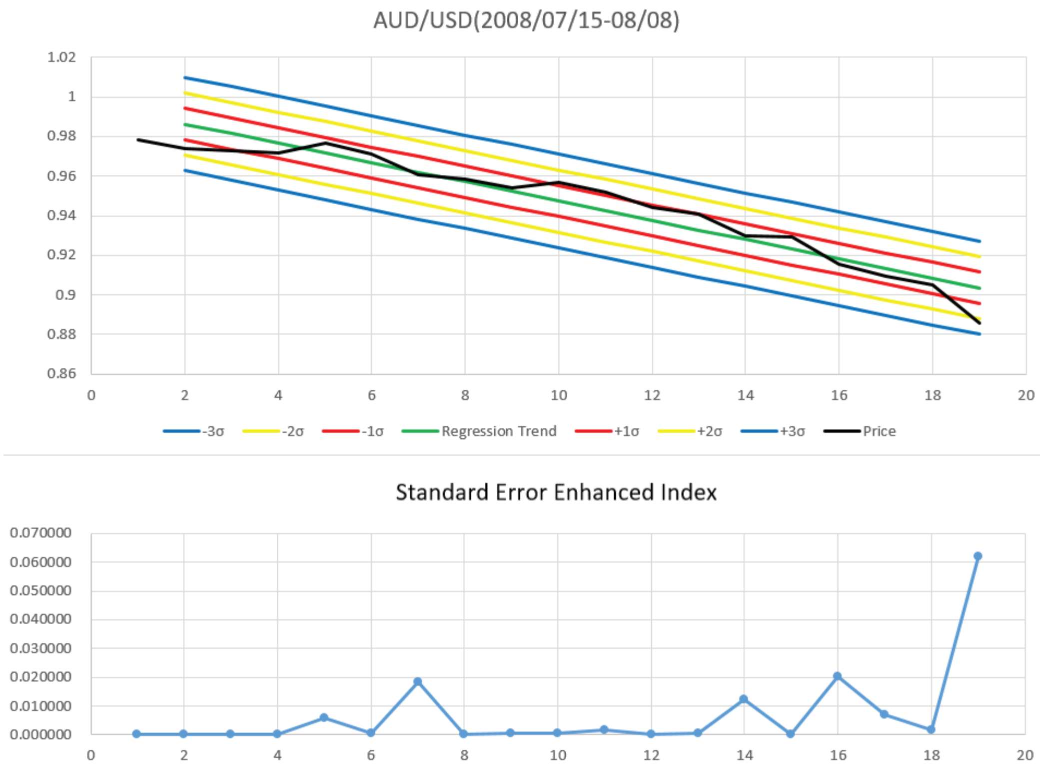
In Figure 16, as the price is declining and hitting new lows, it is assumed that a downtrend is underway. The starting point of the trend is the previous high on July 15, 2008, immediately before the trend.

Figure 16. AUD/USD (2008/05/21—08/04)



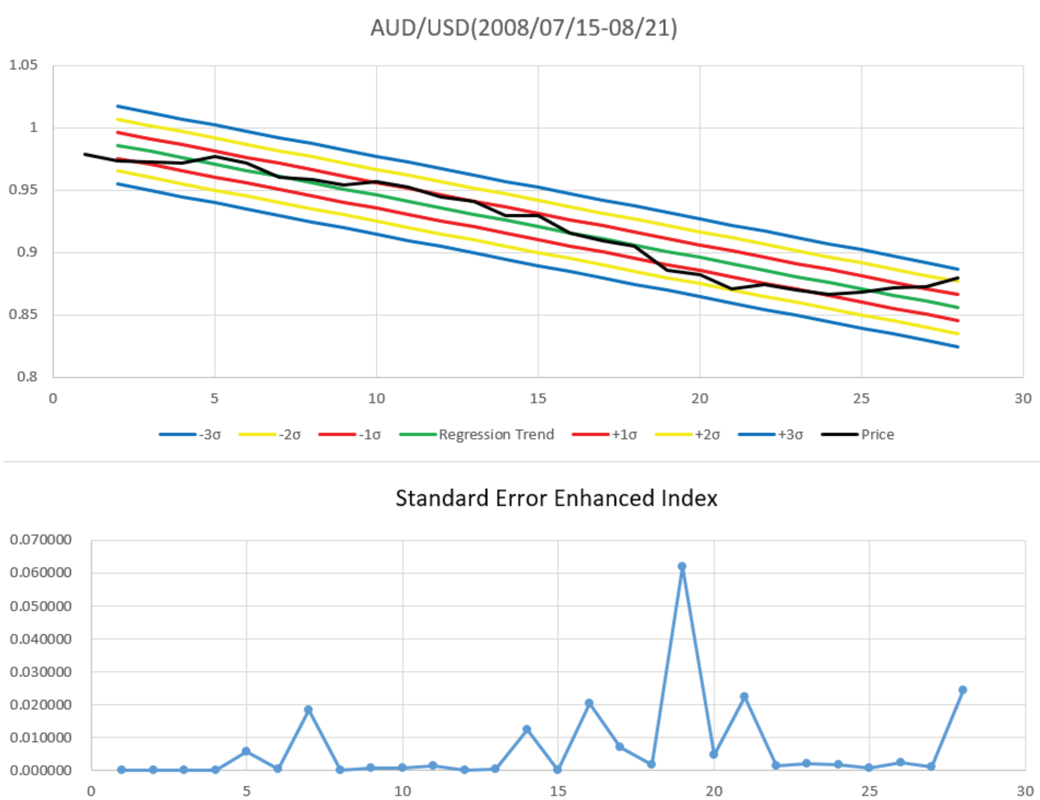
In Figure 17, a yield point is observed due to the increase in the standard error enhanced index.

Figure 17. AUD/USD (2008/07/15–08/08)



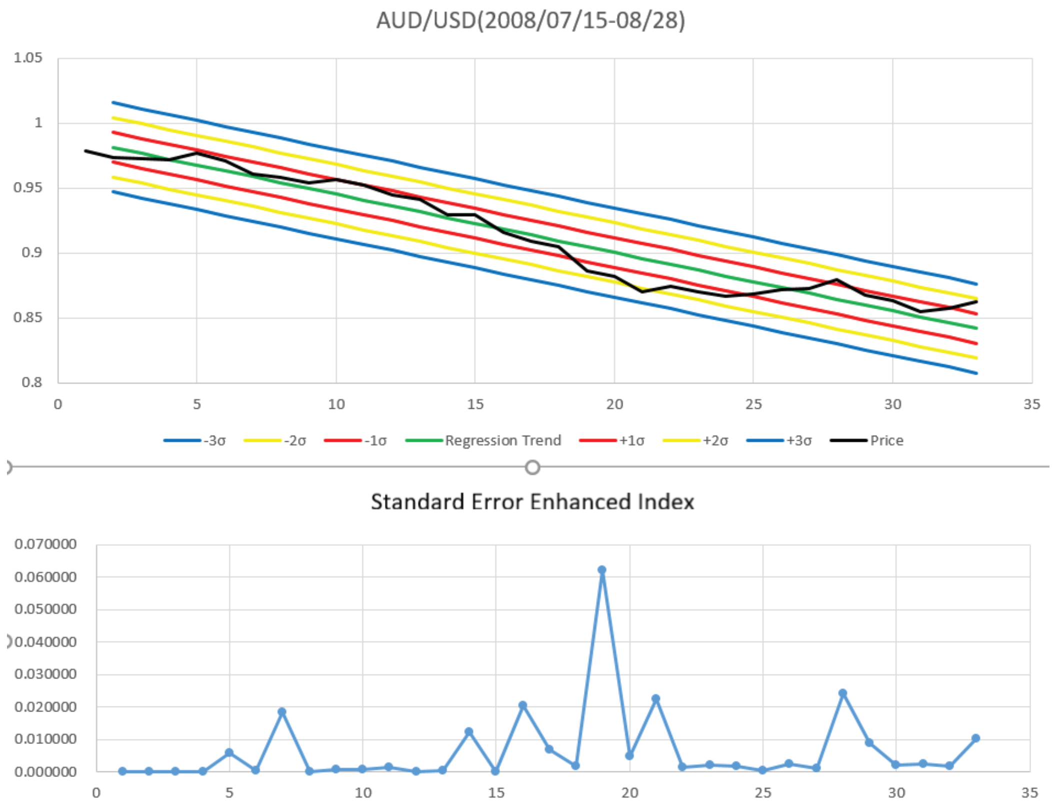
In Figure 18, a yield point is observed due to the increase in the standard error enhanced index. If the closing price continues to rise, it is inferred that the downtrend has come to an end.

Figure 18. AUD/USD (2008/07/15–08/21)



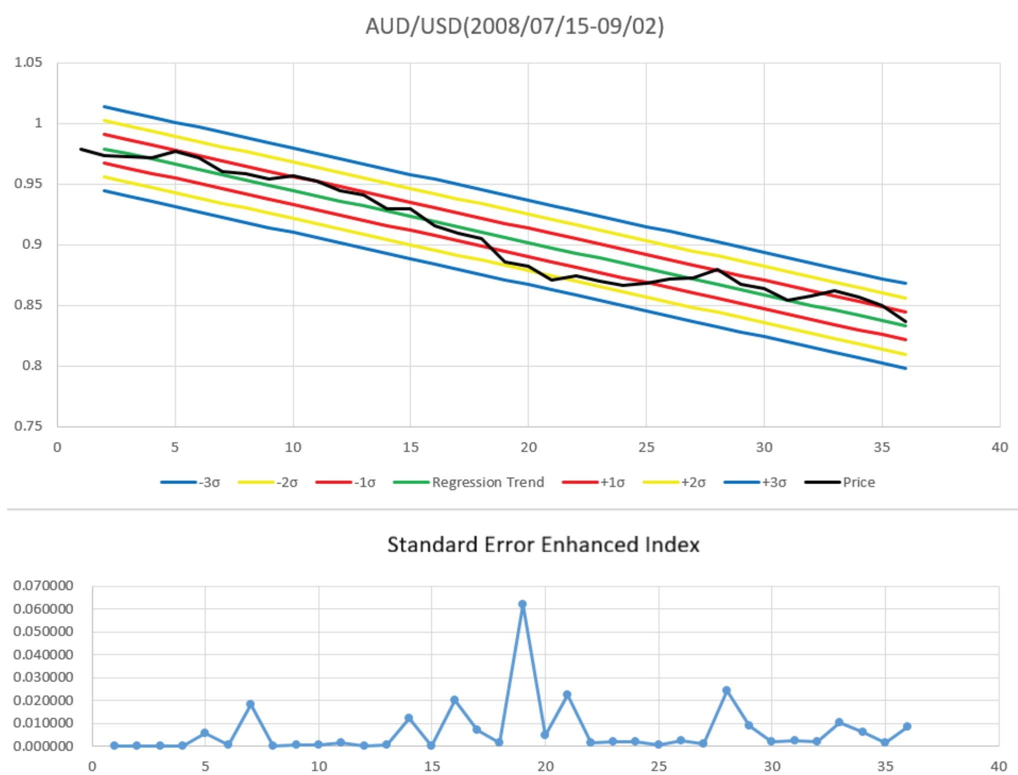
In Figure 19, a yield point is observed due to the increase in the standard error enhanced index.

Figure 19. AUD/USD (2008/07/15–08/28)



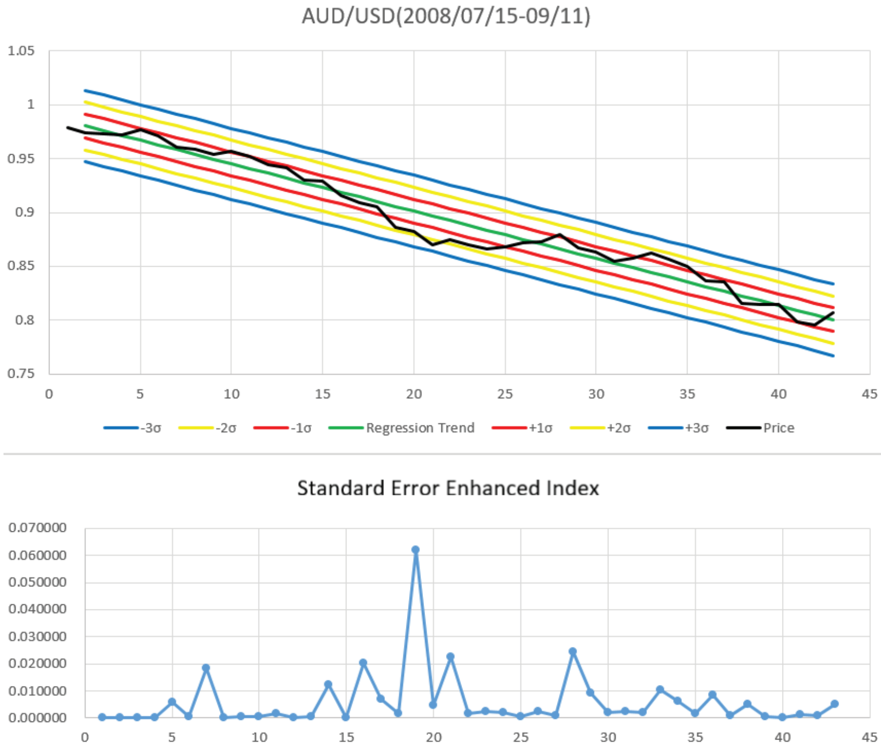
In Figure 20, an increase in the standard error enhanced index is observed, but this is not a yield point because the position of the closing price is not standard error ±2σ.

Figure 20. AUD/USD (2008/07/15–09/02)



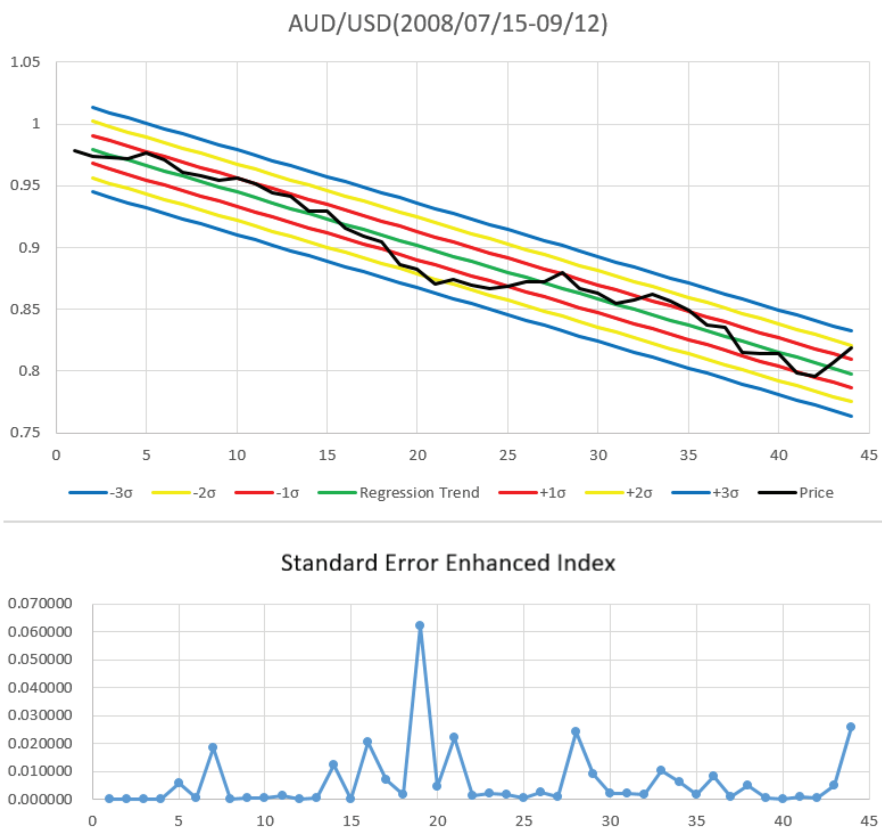
In Figure 21, an increase in the standard error enhanced index is observed, but this is not a yield point because the position of the closing price is not standard error ±2σ.

Figure 21. AUD/USD (2008/07/15–09/11)



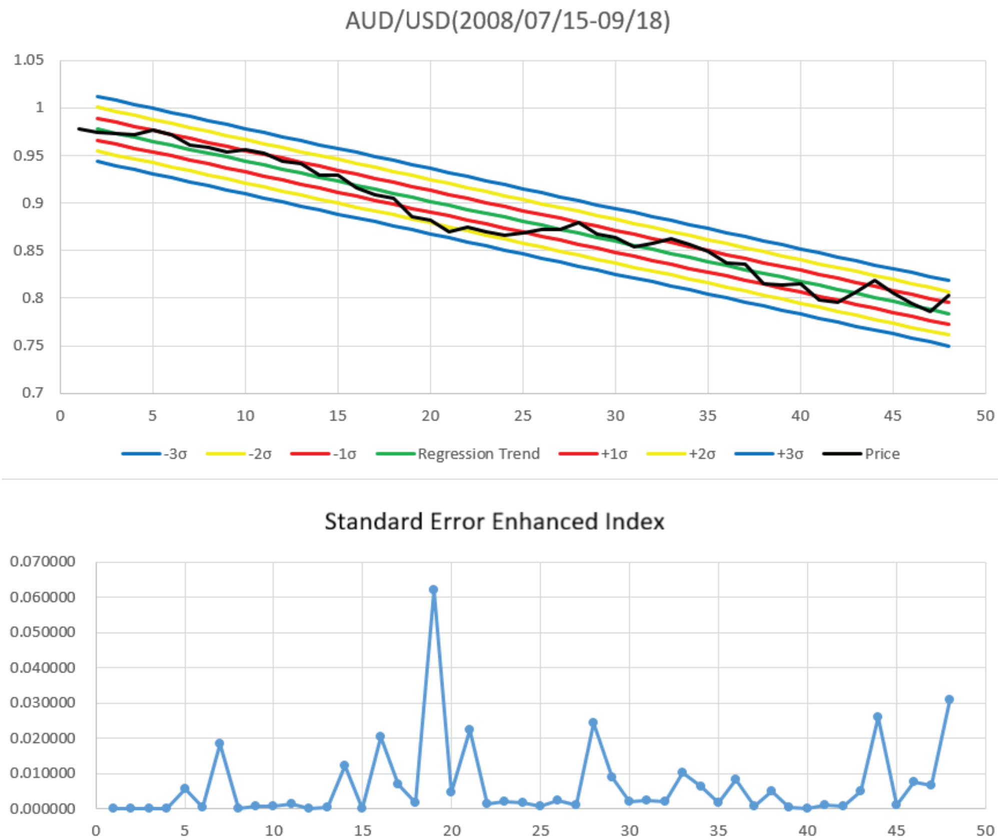
In Figure 22, an increase in the standard error enhanced index is observed, but this is not a yield point because the position of the closing price is not standard error ±2σ.

Figure 22. AUD/USD (2008/07/15–09/12)



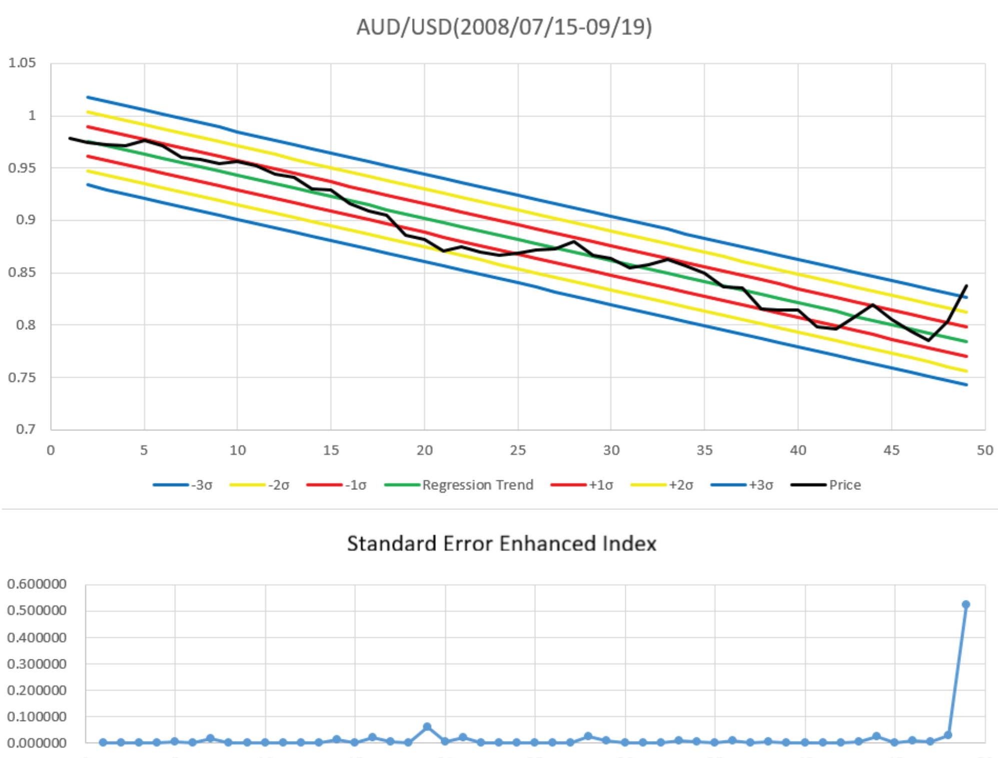
In Figure 23, a yield point is observed due to the increase in the standard error enhanced index.

Figure 23. AUD/USD (2008/07/15—09/18)



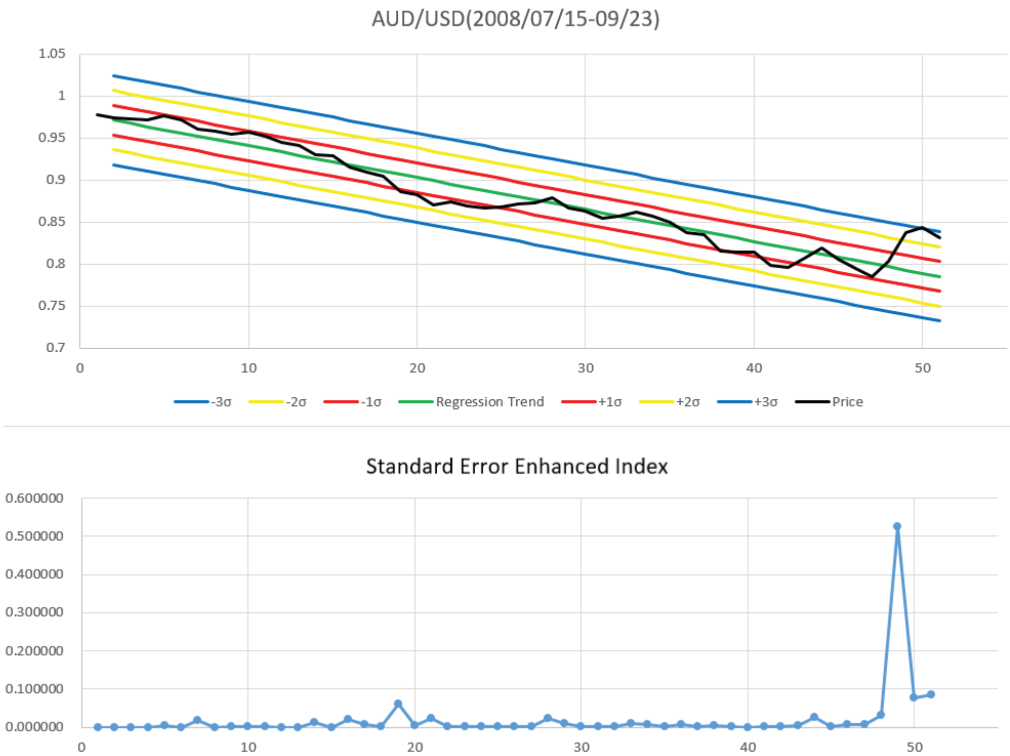
In Figure 24, the yield point observed in Figure 23 has been passed, so the trend is considered to have shifted from the elastic region to the plastic region. In other words, the downtrend is approaching its end.

Figure 24. AUD/USD (2008/07/15—09/19)



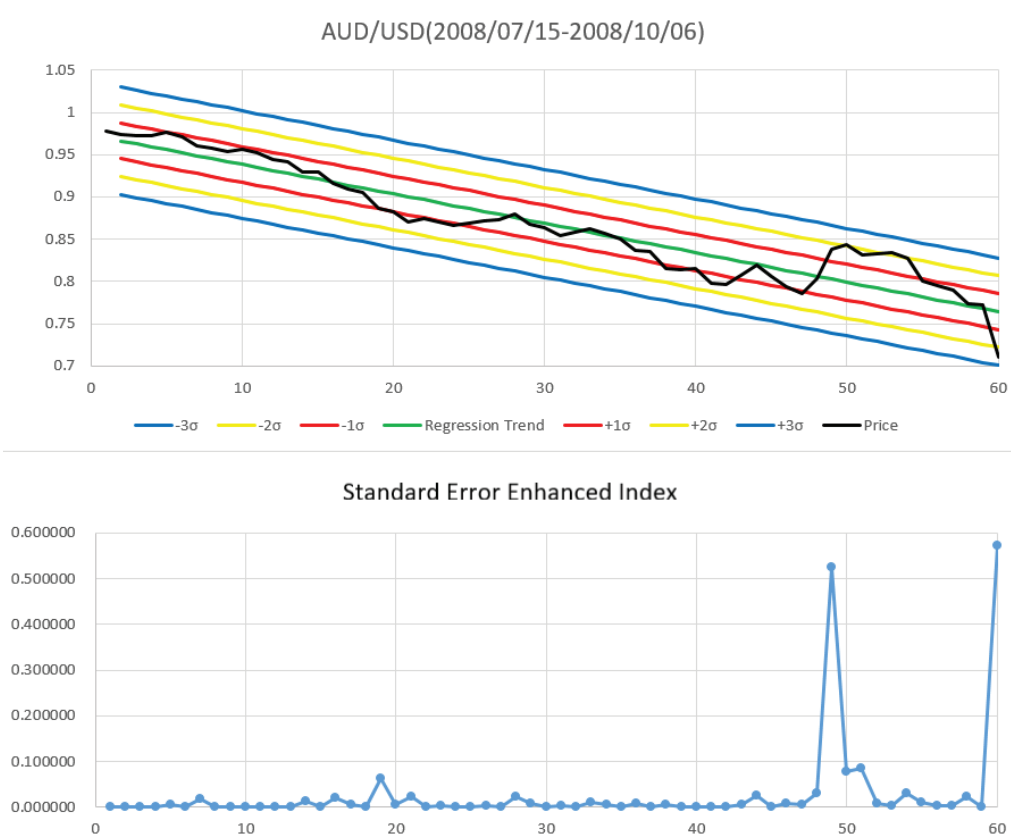
In Figure 25, the yield point of the trend has already been passed, so the closing price is expected to continue rising.

Figure 25. AUD/USD (2008/07/15–09/23)



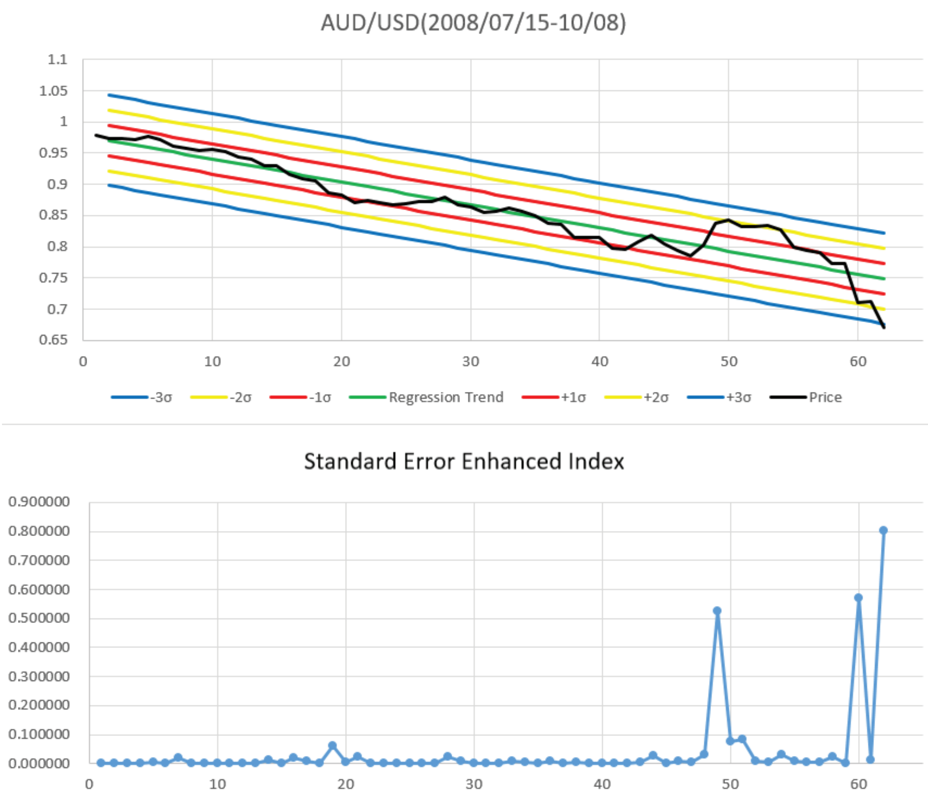
In Figure 26, the closing price has begun falling again and the standard error enhanced index has hit a new high. Therefore, the earlier observed yield point is considered to have been false. The short uptrend seen earlier is thought to have been contained in the downtrend that began on July 15.

Figure 26. AUD/USD (2008/07/15–10/06)



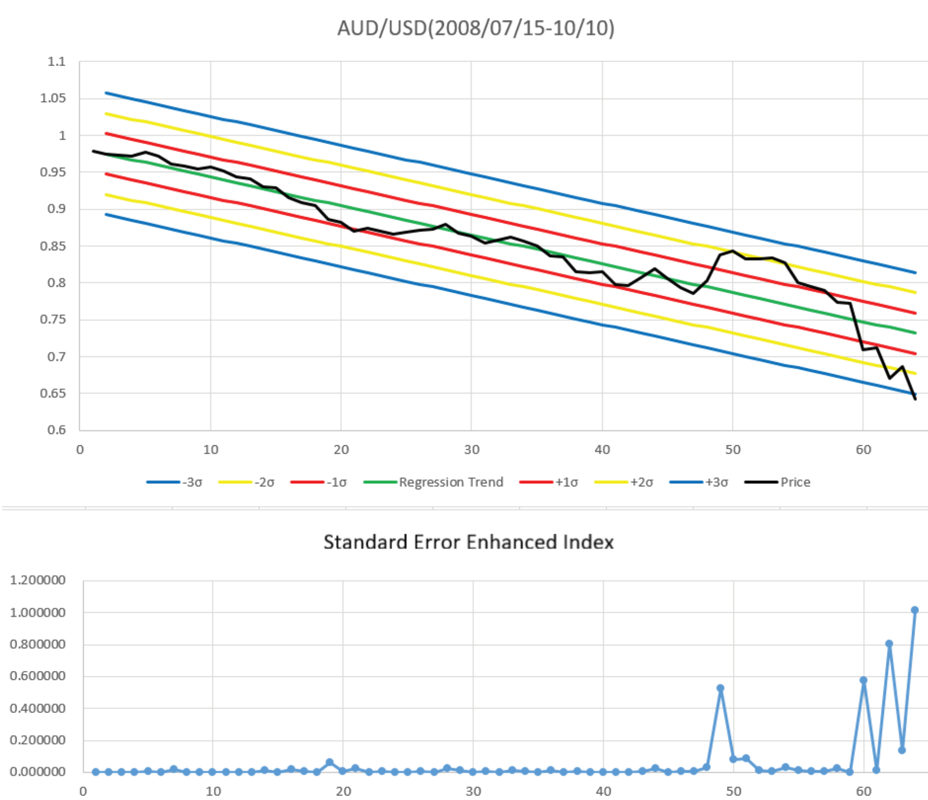
In Figure 27, the yield point observed in Figure 26 has been passed, so the trend is considered to have shifted from the elastic region to the plastic region. In other words, the downtrend is approaching its end.

Figure 27. AUD/USD (2008/07/15–10/08)



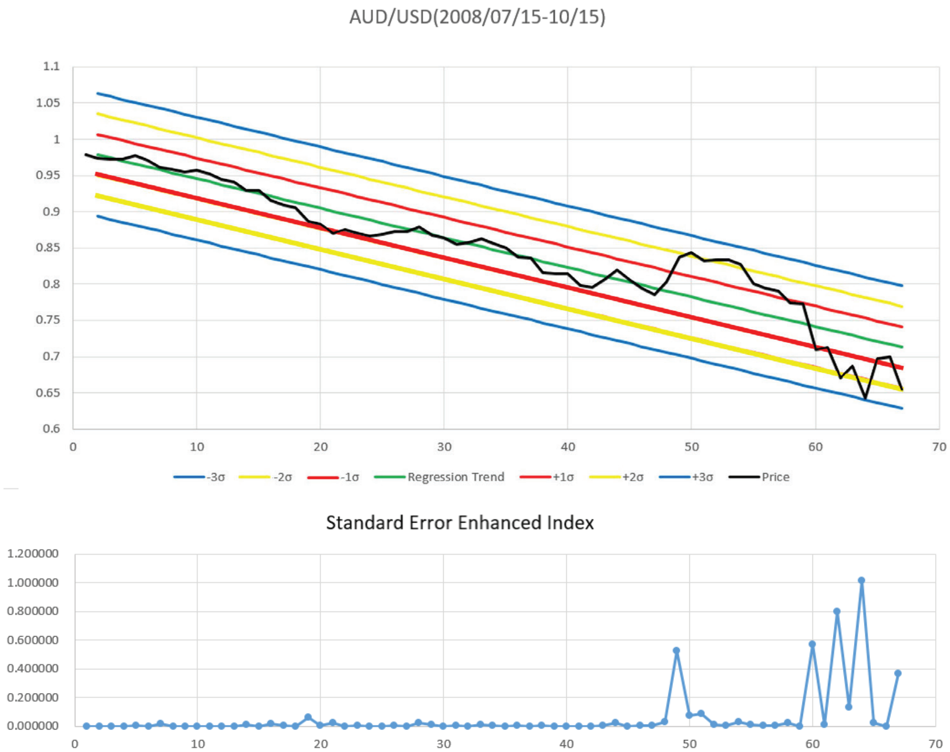
In Figure 28, as long as the closing price continues falling, it is considered that the downtrend is continuing.

Figure 28. AUD/USD (2008/07/15–10/10)



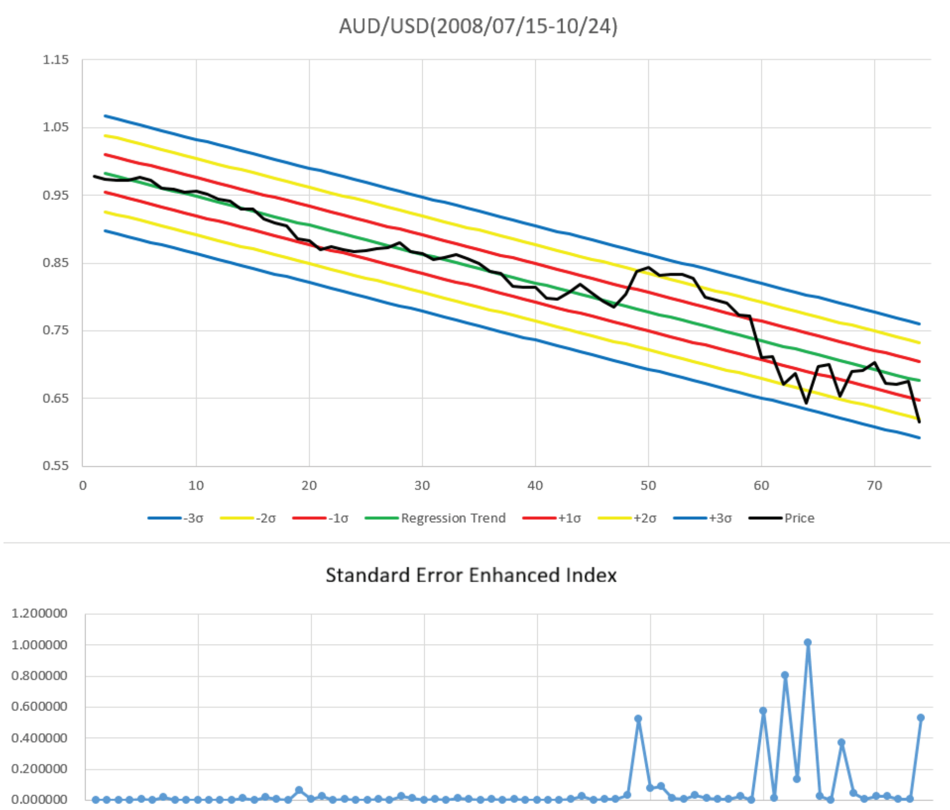
As shown in Figure 29, if both the closing price and the standard error enhanced index hit new values, it is considered that the downtrend is continuing.

Figure 29. AUD/USD (2008/07/15–10/15)



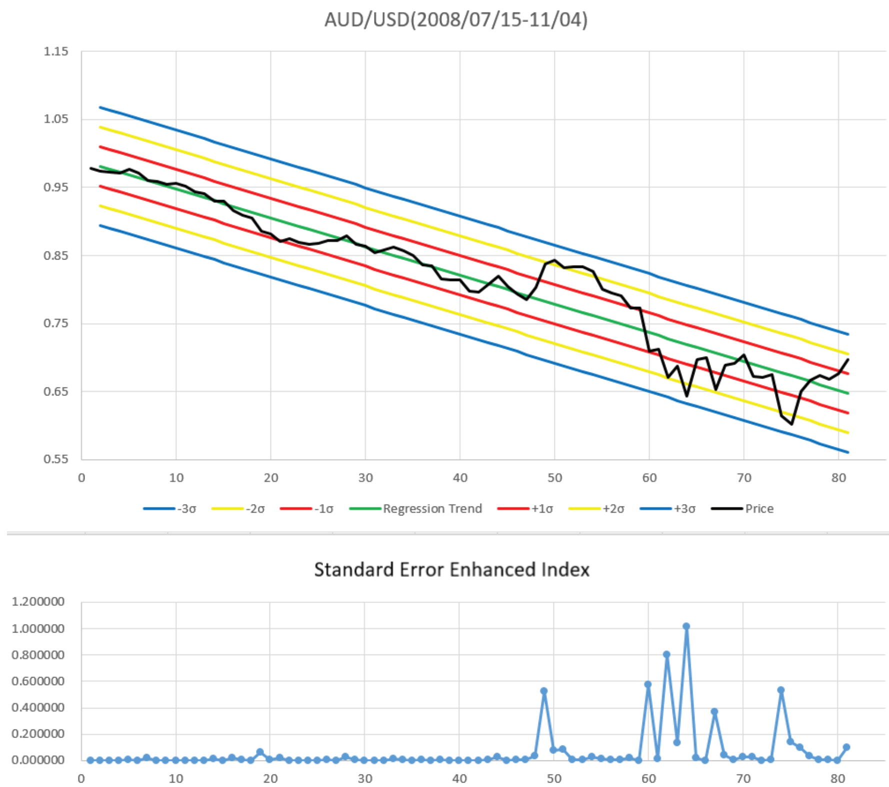
In Figure 30, both the closing price and the standard error enhanced index have hit new values, so it is considered that the downtrend is continuing.

Figure 30. AUD/USD (2008/07/15–08/21)



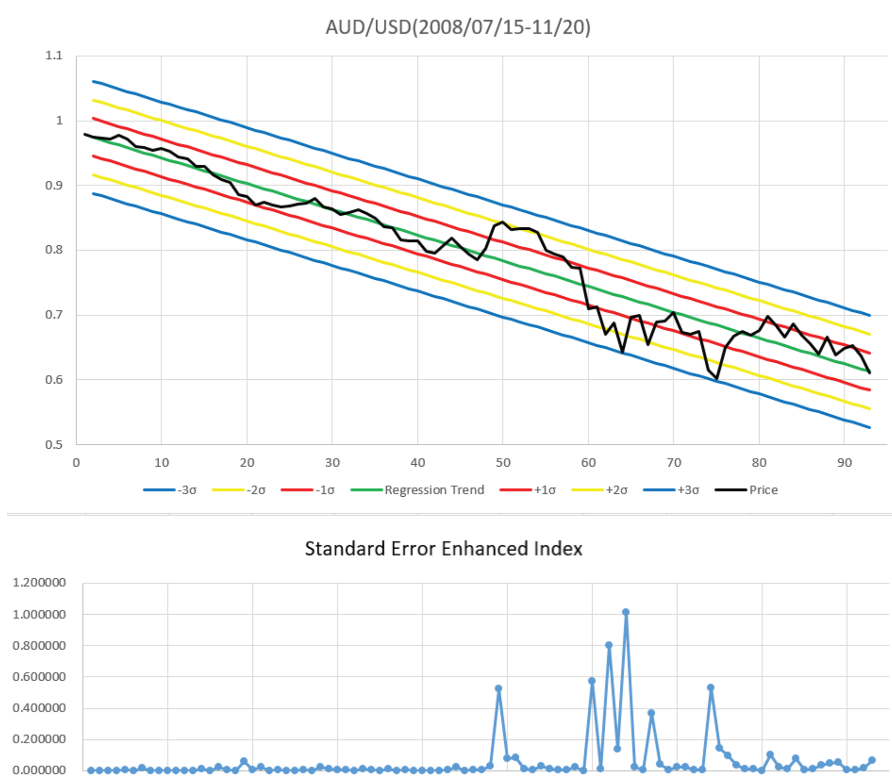
As shown in Figure 31, if the closing price continues to rise and an increase in the standard error enhanced index is observed, it is inferred that the downtrend has come to an end.

Figure 31. AUD/USD (2008/07/15–11/04)



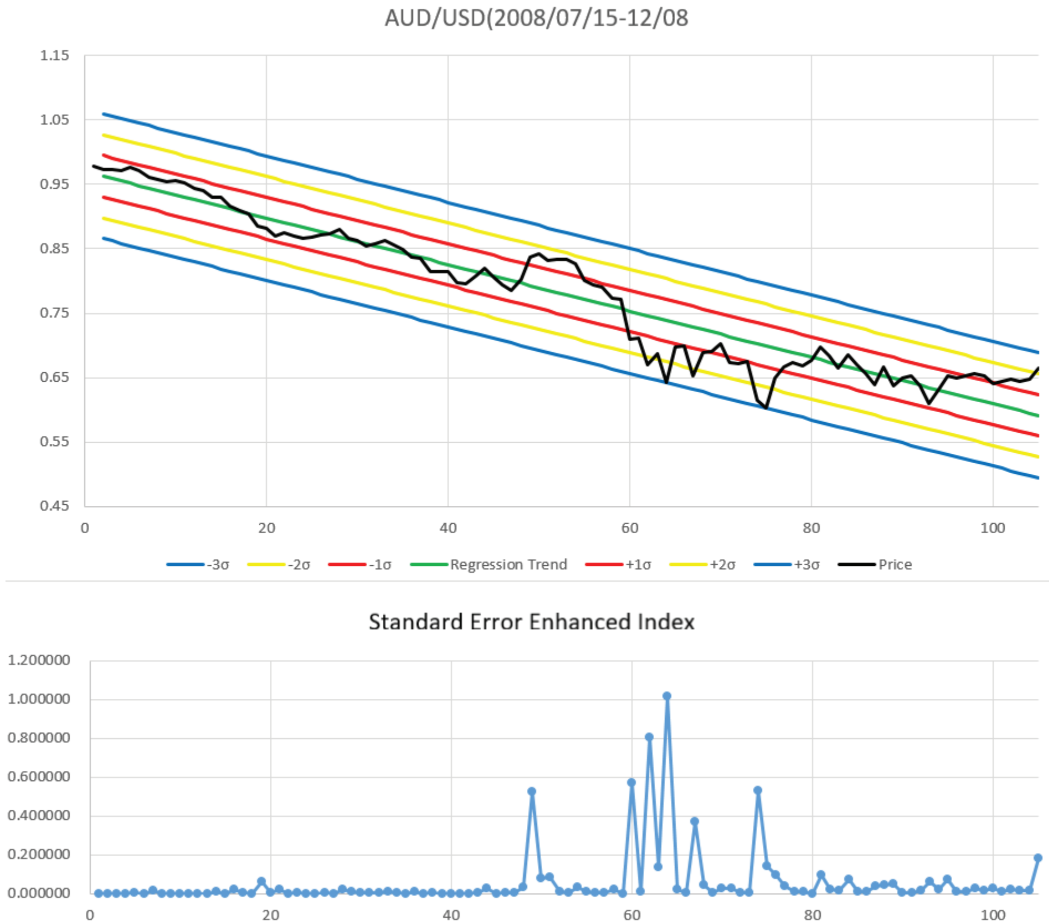
As in Figure 32, if both the closing price and the standard error enhanced index hit new values, it is considered that the downtrend is continuing.

Figure 32. AUD/USD (2008/07/15–11/20)



In Figure 33, because neither the closing price nor the standard error enhanced index hit new values, resumption of the downtrend was not observed. The downtrend is considered to have ended unless a new low is reached.

Figure 33. AUD/USD (2008/07/15–12/08)



Consideration

In this study, I analyzed charts of the Nikkei stock average and AUD/USD by regression trends and the standard error enhanced index. It was found that we can detect the end of a trend by using these two factors. On the other hand, there were cases where a short-term rebound was judged to be the end of the trend, as seen in AUD/USD. It is notable that a rebound occurred after the yield point of the trend was observed in Figure 24. As explained in the section "Factors and the Method," it is necessary to judge that the downtrend has resumed when the price has hit a new low again. I also tested it with CME crude oil futures and obtained similar results to those of AUD/USD. On the contrary, when I tested it with uptrends of AUD/USD, the yield point observation worked as in the case of the Nikkei stock average.

We cannot detect the end of a trend by using regression trends in the way generally explained in literature because an ongoing trend continues to increase the standard error with the lapse of time. It is necessary to use the standard error enhanced index employed in this study in combination with regression trends and to observe the impact of the expansion of the standard error on the trend.

Conclusion

In this study, I utilized regression trends to observe trends and their end points. I also developed the standard error enhanced index to measure the expansion of the standard error. It was confirmed that the end point of a trend can be determined by using them. However, this method seems to work better in an uptrend, so I will continue to improve it. In addition, there may be events in the market big enough to change the trend, so care should be exercised in actual use.

While I used regression trends to observe the yield point of a trend, I believe that regression trends are also compatible with the Elliott wave, cycle analysis, etc. I have a hypothesis that by measuring each Elliott wave by regression trend, the end of the wave can be predicted. I want to work on this study in the future. I also want to study a method to measure a downtrend of a 60-minute candlestick included in an uptrend of daily candlestick. Through my studies in technical analysis, I hope to contribute to the betterment of society. It would be my pleasure if this thesis would be of help to financial traders, sales people, and investors around the world.

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This thesis is the author's personal statement and not the intention of the institution to which he belongs. The institution is in no way responsible for it.

Intraday-Trade-Optimization Via Fibonacci-DLL

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Abstract

The first unsatisfactory thing is that, despite the frequent use of Fibonacci resistance and support lines, the scientific reputation is rather poor. The proof about the mathematical power and functionality is difficult—despite achievable successes. Software manufacturers naturally implement such functionalities in their trading software, which also play a weighty role in the various strategies for trading. However, the question also arises whether it is possible to use simplified empirical methods to determine the turning points in the price development in such a way that there is sufficient time for a trading reaction.

This is done by using statically fixed distances to the current price value (left and right edge) and determining the slope of the moving edge from this. The determination points move continuously at the same distance.

This representation permits a reliable view of the possible turning points. However, this takes place only with course changes. Constant courses over a longer period do not play a role. The effectiveness is proven in my opinion with the following work. The basic data is available for review and can be discussed with more advanced analysis features.

With existing data, the methodology and conclusions drawn from it withstand any resistance. The approach differs significantly from common approaches, as these otherwise allow for significant influence on traders' application of the help and support lines. This approach does not allow for any particular influence and is only variable in the definition of the left and right secant points, keeping the approach methodologically simple and fixed within its framework

Introduction

Fibonacci Number Series

The Fibonacci number series and the ratios derived from it open up the possibility of calculating both striking support points and resistances as well as potential price targets of current movements, adapted in the price trend of stocks and indices. These are often provided in trading systems as functionally adaptable overlays. The Shoulder-Head-Shoulder formation (first and third middle high as Shoulder, middle stronger high as Head) is certainly worth mentioning (see e.g., Savin/Weller/Zvingelis [2003]) but will not play a role in the following.

The discovery of this number sequence goes back to Leonardo Fibonacci da Pisa (1170–1240) and his work "Liber Abaci." The interesting thing about the number sequence is not the result itself, but the relations of the numbers to each other. If one looks at the Fibonacci number ranges: 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 134, 233, 377, 610..., it can be used to determine the irrational number Phi (Φ, ϕ, φ, more rarely tau or g) for the ratio of the golden ratio, which can be used to determine retracements (price corrections at resistance and support lines) and extensions (price movements that strongly exceed the previous impulse). However, Kempen already stated or proved in his 2015 paper "Fibonaccis are Human (made)" that a) price reversal is most likely for all trend classes in the range of 50% of the movement, b) trend correction is more likely than trend break regardless of trend class, and c) there is no empirical reason for the restriction to a few excellent retracement levels. This last point means that 100% retracement is not empirically confirmed as a support line because there is no clear statistical significance for any trend class and, most importantly, the significance of Fibonacci retracements is empirically refuted for all trend classes. However, the 100% level is significant in a small environment, but the size of this environment depends on the trend class and is opposite to the trend duration. The same applies in a weakened way to the 33%, 50%, and 67% levels for secondary and tertiary trends (see Kempen [2015], p. 21). The calculation is carried out via the quotient formation with the limit value consideration (Kempen [2015], p. 10):

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

and following also (cf. Gaucan/Maiorescu [2011], McLean [2005]).

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

$$F_3 = \ldots \approx 0.236067$$

He clearly concludes that the "empirical investigations [...] have exposed the myth of Fibonacci retracements as human (made). Moreover, it has been shown that the choice of retracement forecasts can be optimized with the help of empirical evaluations. Although the recommendations set by Murphy [...] are a good choice, added value has been created with the (cumulative) probability trajectories produced." (Kempen [2015], p. 22) Although mathematically refuted to a large extent, it is empirically consistent in use, because including Kempen, one can postulate that the inclusion of auxiliary lines in the price observation of stocks very well expresses a certain probability that a trend reversal is imminent. This is no proof and no guarantee, especially since the price development depends on the actions of the market participants and expresses the expectation horizon of these. Nevertheless, the presentation of trend lines shows that statistically significant supports are useful in anticipating the possible course of the price. This does not have to be done using explicit Fibonacci-based lines; it can be other line definitions, but Fibonacci lines can also be considered valuable.

If we look at trading software (i.e., professional trading systems), we can see that the inclusion of trend lines is a common practice and is recognized as beneficial. Thus, there are many traders who have their trading strategy supported by Fibonacci lines for both short and long-term trends (see McLean [2005], p. 12ff). However, this must also be understood in terms of content. "It is our job to interpret a chart and then to translate that interpretation into a language that is understood by the non-professional technical analyst, keeping it as simple and jargon-free as possible. Anyone can draw a trendline; only a few can interpret Elliott wave or Gann theories." (McLean [2005], S. 30)

Fibonacci Ratios

Fibonacci retracements indicate potential support and resistance levels. If the range of a previous price swing is only corrected, it is a retracement, but if this range is exceeded ("extended"), it is an extension. For the representation of the retracements with the upward trend, the low point (100% retracement) is first connected with the following high point (0% retracement). With the difference of these two points, starting from the high point, the retracements are measured in percentages of 23.6%, 38.2%, 50%, 61.8%, and 78.6% and drawn in as a horizontal line by the trading software. For plotting the retracements on the downtrend, it is the converse, but with the lines 127.2%, 150%, and 161.8%, for example. These are the most favored lines for support (see also Prasad [2010], pp. 16ff, 54ff).

The most favored line is that of the 61.8% retracement as the critical zone, which signals whether a current swing is a countertrend swing or a swing into a new trend direction. Thus, countertrends or corrections should not cross the 61.8% retracement. However, if it is exceeded, it is usually assumed that the market is taking a new trend direction and is not just a countertrend. Here, however, one must object that the 61.8% retracement represents an important potential support or resistance, but cannot always be seen as a trend signal, because it is not uncommon for a wave to end at a 78.6% retracement before the next strong wave starts. For this reason, a 78.6% price correction is also an important retracement level that should not be undercut, provided the previous trend direction is continued.

Ultimately, this methodology can be used in intraday trading as well as in long-term market monitoring to locate potential trend direction changes.

Materials and Methods

Approach of Change Points on the Time Axis

In the following, a supplementary approach shall be presented that does not include all trend components of the price course, but only includes the price changes and anticipates the further course from this via Fibonacci lines.

This approach is to set a marker at the points with a higher probability that the price trend will rise or fall. This can also be used to identify small jumps. The procedure shows that its use can be empirically proven.

By means of a small example, the procedure shall first be explained. In the following are the date format dd.mm.yyyy and the time format hh:mm (german).

Figure 1. Adidas share price performance as of March 31, 2021

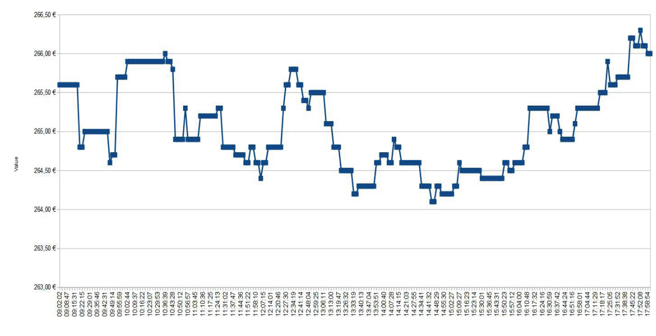


Figure 1 shows the price development of the Adidas share in the period from 9:00 in the morning to 18:00 in the evening for March 31, 2021. In addition to the phases of rise and fall, the constant values over longer periods can also be seen here. In the period from around 10:02 to 10:34, for example, the share price is unchanged at EUR 265.90.

Figure 2. Change points of the Adidas share price development from 31.03.2021

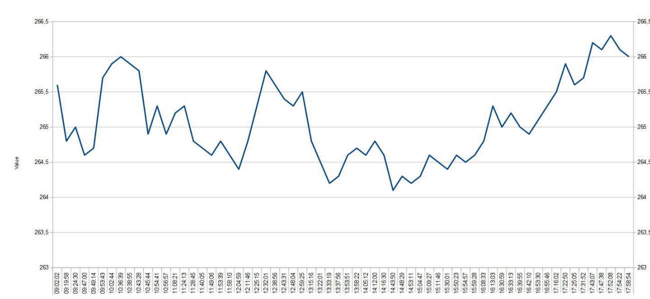


Figure 2 again shows only the change points with the change values of Adidas. It is therefore an identical representation in terms of content as Figure 1, but the phases of constant values are not included.

Table 1. Excerpt of the Adidas price history as of 31.03.2021 with consideration in Figures 1 and 2

Date	Name	Timestamp	Value	Chk	Dataset incl. in Figure 1	Dataset incl. in Figure 2
31.03.2021	adidas	08:59:47	264,20 €	x	x	x
31.03.2021	adidas	09:02:02	265,60 €	x	x	x
31.03.2021	adidas	09:04:18	265,60 €	_	x	
31.03.2021	adidas	09:06:32	265,60 €	_	x	
31.03.2021	adidas	09:08:47	265,60 €	_	x	
31.03.2021	adidas	09:11:02	265,60 €	_	x	
31.03.2021	adidas	09:13:17	265,60 €	_	x	
31.03.2021	adidas	09:15:31	265,60 €	_	x	
31.03.2021	adidas	09:17:45	265,60 €	_	x	
31.03.2021	adidas	09:19:58	264,80 €	x	x	x
31.03.2021	adidas	09:22:15	264,80 €	_	x	
31.03.2021	adidas	09:24:30	265,00 €	x	x	x
31.03.2021	adidas	09:26:46	265,00 €	_	x	
31.03.2021	adidas	09:29:01	265,00 €	_	x	
31.03.2021	adidas	09:31:15	265,00 €	_	x	
31.03.2021	adidas	09:33:29	265,00 €	_	x	
31.03.2021	adidas	09:35:46	265,00 €	_	x	
31.03.2021	adidas	09:38:01	265,00 €	_	x	
31.03.2021	adidas	09:40:17	265,00 €	_	x	
31.03.2021	adidas	09:42:31	265,00 €	_	x	
31.03.2021	adidas	09:44:45	265,00 €	_	x	
31.03.2021	adidas	09:47:00	264,60 €	x	x	x
31.03.2021	adidas	09:49:14	264,70 €	x	x	x
31.03.2021	adidas	09:51:29	264,70 €	_	x	
31.03.2021	adidas	09:53:43	265,70 €	x	x	x
31.03.2021	adidas	09:55:59	265,70 €	_	x	
31.03.2021	adidas	09:58:13	265,70 €	_	x	
31.03.2021	adidas	10:00:27	265,70 €	_	x	
31.03.2021	adidas	10:02:44	265,90 €	x	x	x
31.03.2021	adidas	10:05:02	265,90 €	_	x	

In this respect, there are fewer points in the price history to consider, but the informative value of this representation is the same with fewer time stamps. The relevant price changes can be identified more quickly, even with small jumps. This view forms the basis for further development. There is also a large number of IT systems that do not offer such support lines (e.g., in the field of energy trading). The further explanations can serve as a basis for this, and the results can be integrated there later.

Derivation of the Markers

The current price value forms the reference point. The trend line is generated, for example, with a 2_8 F-step definition from the value two points back as the right value and, starting from this, the point eight further values back as the left value. Thus, the relations of the trend development to the current value are to be represented in the following:

* 2_8: Right value two values before the current value standing, from this, eight values to the left running as left value defined,

* 1_8: Analog one value in front of the current value, eight values running from this to the left,

* 2_10: Analog two values before the current value, 10 values running from this to the left,

* 2_5: Analog two values before the current value, five values running from it to the left, etc.

If the right point in the value is larger than the left point, a positive gradient of the trend results; if this is not so, it concerns a negative trend (fiboricht = Direction). From these two values (left and right) in dependence of the trend direction, the expected Fibonacci reference values are determined from the difference between right and left value as absolute value (abs [right-left]). The calculation in LAZARUS looks as follows:

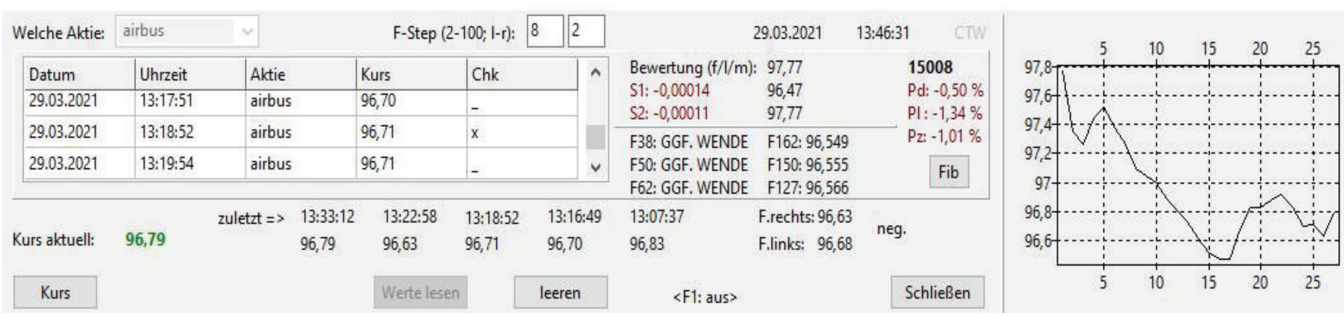
(Wildensee [2021a]), Source Code from procedure TForm1.
Fibo1;

Table 2. Excerpt of Source Code Fibonacci Limits

```
[...]
   diff1:=abs(wertmax1-wertlow1); // positiver Wert der Differenz (absolut); right=wertmax1
   if (fiboricht = true) then               // bei positiver Steigung; left=wertlow1
    begin
     fibborder62:=wertmax1-(((wertmax1-wertlow1)*62)/100); // rounded
     fibborder50:=wertmax1-(((wertmax1-wertlow1)*50)/100);
     fibborder38:=wertmax1-(((wertmax1-wertlow1)*38)/100);
     fibborder162:=wertmax1+(((wertmax1-wertlow1)*162)/100);
     fibborder150:=wertmax1+(((wertmax1-wertlow1)*150)/100);
     fibborder127:=wertmax1+(((wertmax1-wertlow1)*127)/100);
    end;
   if (fiboricht = false) then  // bei negativer Steigung
    begin
     fibborder62:=wertmax1+(((wertlow1-wertmax1)*(100-62))/100); // different showing
     fibborder50:=wertmax1+(((wertlow1-wertmax1)*50)/100); // in 62+38 invers showing
     fibborder38:=wertmax1+(((wertlow1-wertmax1)*(100-38))/100); // without dec. point calculation
     fibborder162:=wertmax1-(((wertlow1-wertmax1)*162)/100);
     fibborder150:=wertmax1-(((wertlow1-wertmax1)*150)/100);
     fibborder127:=wertmax1-(((wertlow1-wertmax1)*127)/100);
    end;
[...]
```

In case of a negative slope, it is necessary to swap the display labels for the Fibonacci limits in the value 38 and 62 (inverse showing); otherwise, a wrong order will be displayed. This is not mandatory, but it makes sense for the display in order not to confuse. Thus, the program can be represented first as shown in Figure 3.

Figure 3. Example representation, German version, of the program development (rising phase)



It can be seen in Figure 3 that the price values are read continuously (every half minute), the change points are marked with an "x" in the Chk (Check) field, and only these are shown in the price development. Base values like the first value (f), lowest value (l), and maximum value (m), and also values for slope (S1 for first-middle slope and S2 for first-low slope) and return (Pd for average-min-return, Pl for max-average-return, and Pz for max-min-return), are provided. Via the "Fib" button, other F-Step values can also be used for a short time (after switching off the update cycle) to recognize the Fibonacci values (F-Step = left and right value), and the last five Change values are provided with the current value. The values are taken from a rounded point of view (i.e., the decimal places are not included) because this is too small.

The calculation of the potential turning points (the labels are empty at the time) results as follows: (source code from procedure TForm1.Fibo1).

Table 3. Excerpt of source code Fibonacci derivation of potential turning points

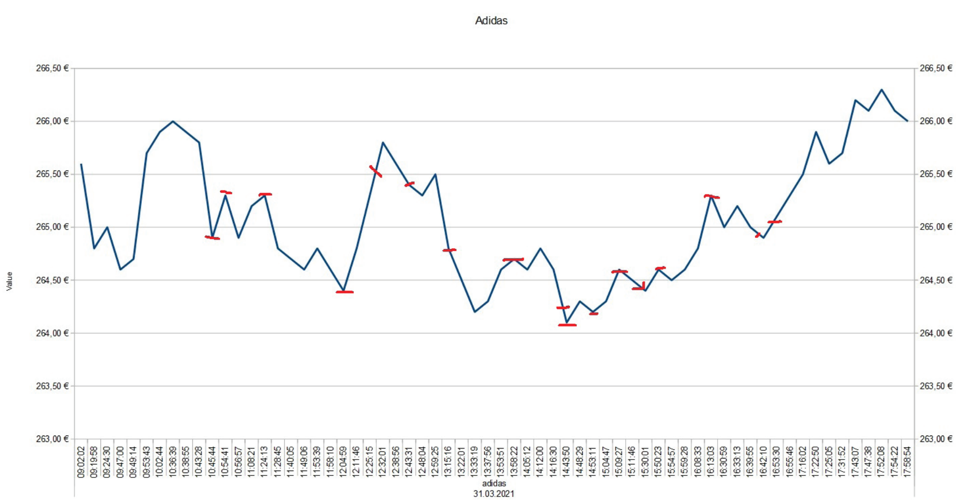
```
[...]
   LabelFib38.Caption:='F38:  '+copy(FloatToStr(fibborder38),1,6);
   LabelFib38.Refresh;
   LabelFib50.Caption:='F50:  '+copy(FloatToStr(fibborder50),1,6);
   LabelFib50.Refresh;
   LabelFib62.Caption:='F62:  '+copy(FloatToStr(fibborder62),1,6);
   LabelFib62.Refresh;
   LabelFib162.Caption:='F162:  '+copy(FloatToStr(fibborder162),1,6);
   LabelFib162.Refresh;

   LabelFib150.Caption:='F150:  '+copy(FloatToStr(fibborder150),1,6);
   LabelFib127.Caption:='F127:  '+copy(FloatToStr(fibborder127),1,6);
   LabelFib127.Refresh;
   if ((fibohricht = true) and (length(LabelNewValue.Caption)>0)) then // positive direction
    begin
    if ((StrToFloat(LabelNewValue.Caption) <= fibborder62) and (fibborder62 <> 0)) then
      begin
       LabelFib62.Caption:='F62: CHANGE?';
       LabelFib62.Refresh;
      end;
     if ((StrToFloat(LabelNewValue.Caption) <= fibborder50) and (fibborder50 <> 0)) then
      begin
       LabelFib50.Caption:='F50: CHANGE?';
       LabelFib50.Refresh;
      end;
     if ((StrToFloat(LabelNewValue.Caption) <= fibborder38) and (fibborder38 <> 0)) then
      begin
       LabelFib38.Caption:='F38: CHANGE?';
       LabelFib38.Refresh;
      end;
     if ((StrToFloat(LabelNewValue.Caption) >= fibborder162) and (fibborder162 <> 0)) then
      begin
       LabelFib162.Caption:='F162: CHANGE?';
       LabelFib162.Refresh;
      end;
     if ((StrToFloat(LabelNewValue.Caption) >= fibborder150) and (fibborder150 <> 0)) then
      begin
       LabelFib150.Caption:='F150: CHANGE?';
       LabelFib150.Refresh;
      end;
     if ((StrToFloat(LabelNewValue.Caption) >= fibborder127) and (fibborder127 <> 0)) then
      begin
       LabelFib127.Caption:='F127: CHANGE?';
       LabelFib127.Refresh;
      end;
     end;
   if ((fiboricht = false) and (length(LabelNewValue.Caption)>0)) then // negative direction
    begin
     if ((StrToFloat(LabelNewValue.Caption) >= fibborder62) and (fibborder62 <> 0)) then
      begin
       LabelFib62.Caption:='F62: CHANGE?';
       LabelFib62.Refresh;
      end;
     if ((StrToFloat(LabelNewValue.Caption) >= fibborder50) and (fibborder50 <> 0)) then
      begin
       LabelFib50.Caption:='F50: CHANGE?';
       LabelFib50.Refresh;
      end;
     if ((StrToFloat(LabelNewValue.Caption) >= fibborder38) and (fibborder38 <> 0)) then
      begin
       LabelFib38.Caption:='F38: CHANGE?';
       LabelFib38.Refresh;
      end;
     if ((StrToFloat(LabelNewValue.Caption) <= fibborder162) and (fibborder162 <> 0)) then
```

```
        begin
         LabelFib162.Caption:='F162: CHANGE?';
         LabelFib162.Refresh;
        end;
       if ((StrToFloat(LabelNewValue.Caption) <= fibborder150) and (fibborder150 <> 0)) then
        begin
         LabelFib150.Caption:='F150: CHANGE?';
         LabelFib150.Refresh;
        end;
       if ((StrToFloat(LabelNewValue.Caption) <= fibborder127) and (fibborder127 <> 0)) then
        begin
         LabelFib127.Caption:='F127: CHANGE?';
         LabelFib127.Refresh;
        end;
       end;
[...]
```

Since the constant phases of the value (i.e., over a certain period of time with identical value) can last shorter or also longer, a slope of the successive points is suggested, which is not actually present. Therefore, the actual gradient is also represented under S1 and S2. However, this is not intended otherwise. The tool to be developed is not intended to highlight the reality; this is already done by the main application that integrates this functionality. Rather, it is intended to show the change points in relation to each other and to the trend to be assumed. To view an initial result, Figure 4 shows the trend from Figure 2, but with possible inflection points from the March 31, 2021, calculation.

Figure 4. Change points in the Adidas share price from 31.03.2021 with possible turning points with 2_8



First of all, it can be seen that the beginning phase does not generate any markers. The next phase then shows a price loss with reference to the trend, which leads to a minimum at around 12:00. Subsequently, the price rises strongly, so that the previous markers actually represent entry points for buying as turning points for this day. Afterwards, a falling price development is indicated again. Around 15:00, a phase of increase begins again, but the high around 17:50 is no longer marked. The recognized need for adjustment shows that beside the main line, which was defined as a 2_8 line, an additional correcting auxiliary line is needed, which—as a differentiated definition—shows the developments, which are not recognized from the main line.

The program was redesigned and extended accordingly, so that values are also available at the beginning after a short time. As long as one cannot go back suitably, the first value is used. The source code for this looks as follows:

Source code from procedure TForm1.RangeFiboErmitteln;// Identify left and right border

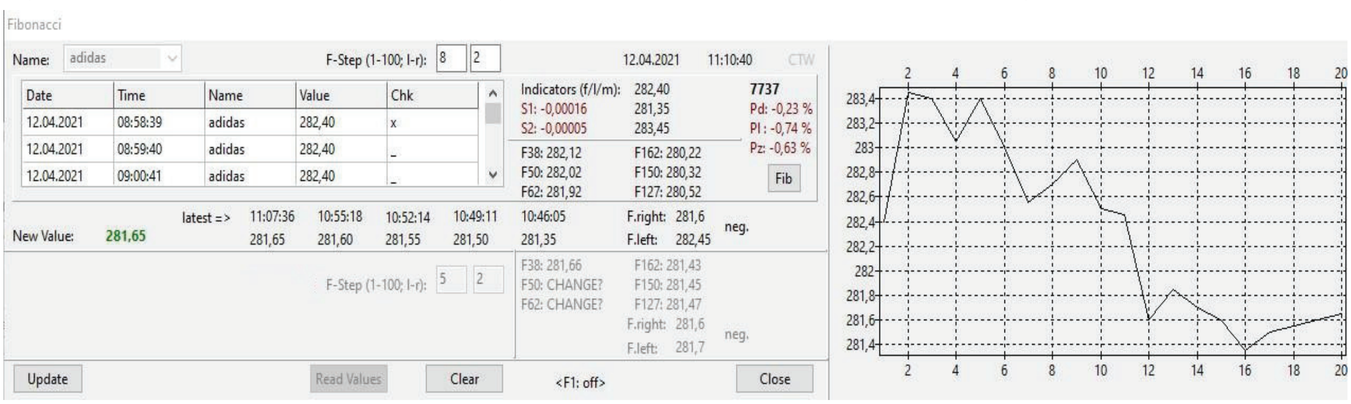
Table 4. Excerpt of source code definition of the two trend outer values

```
[...]
  i:=StringGridValues.RowCount;  k:=0;
[...]
  if (i > 0) then
   begin
    for t:=i-1 downto 1 do
     begin
      if ((TRIM(StringGridValues.Cells[4,t]) = 'x')) then
       begin
        k:=k+1;              // Counter for relevant Values
        if (k = fstep0) then  // Edit of right Value, mostly 2
          begin
           wrechts:=StringGridValues.Cells[3,t]; // right Value
          end;
        if (k = fstep1+fstep0) then  // when k = right Value + left Value, then
          begin  // 8 as default, left and right Value can be changed between 2 and 100
           wlinks:=StringGridValues.Cells[3,t];
          end;
       end;
      if (length(wlinks)<2) then wlinks:=ersterwert;
[...]
     end;
   end;
[...]
```

However, this would also be the case if no values are provided abruptly at a later time. Thus, the provision should only occur if no values for the left boundary arise in the initial phase.

In addition, a second Fibonacci line was drawn in as auxiliary line, which should have another verification mode, so beside e.g., 2_8 still 1_5. The consequence would be that identifications not occurring in the first line are recognized with the second line.

Figure 5. Example representation of the program development after adaptation with change point display



Development of a DLL for Trend Analysis

The result is provided as a Dynamic Link Library, or DLL, so that it can be included in software products as supplementary functionality. "A DLL is a library that contains code and data that can be used by more than one program at the same time." (https://docs.microsoft.com/en-us/troubleshoot/windows-client/deployment/dynamic-link-library). The DLL is to be downloaded under Wildensee (2021b) as a free program. A "kurse.dll" is provided for German support without second auxiliary line, and a "fiboengl.dll" as an English-language version, in the listing single without second auxiliary line, in the listing double with second auxiliary line. Especially the latter should be integrated into other software products.

Results

Data Collection and Initial Evaluation

In the period from March 31 to April 14, 2021, several runs were conducted to collect stock price data using the test tool created for this purpose. In total, the following data was collected for the shares

- Adidas
- Airbus
- Allianz
- BASF
- Bayer
- Bechtle
- BMW
- Evonik
- Fresenius
- GEA

Price data was determined, processed in table processing, and presented in price change graphs. Since results are available for the different lines 2_8, 2_10, 2_12, 1_8, and 2_5, covers of the turns to the trend could be identified. The error rate of the determined datasets is max. 2.5% so that a solid data basis can be assumed.

First, several 2_8 histories as of April 1, 2021, are to be presented. They show that the adjustments in the program logic were important, because errors in the view still occurred here.

Figure 6. Airbus price development on April 1, 2021, change points

Figure 6 clearly shows that no changes were detected in the front area until about 12:00. The early beginning of the rise would have been an entry point. From approximately 13:00, the change points with 2_8 (red) and 2_10 (green) were recognized; 2_10 advances here to the possible auxiliary line.

Figure 7. Allianz share price development on April 1, 2021, change points

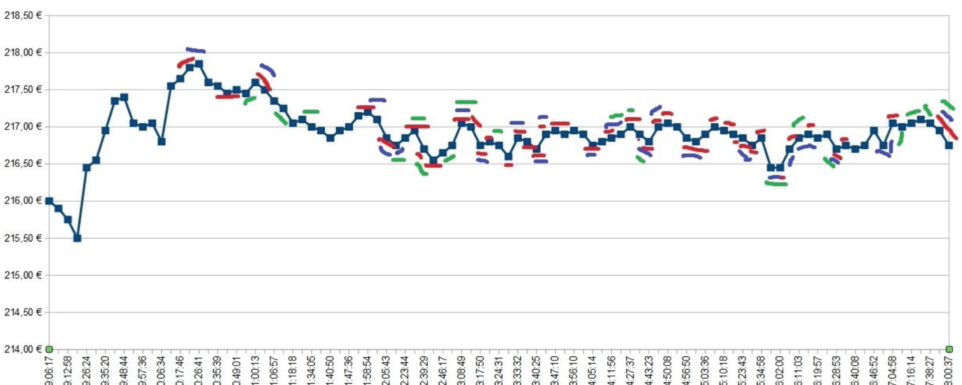
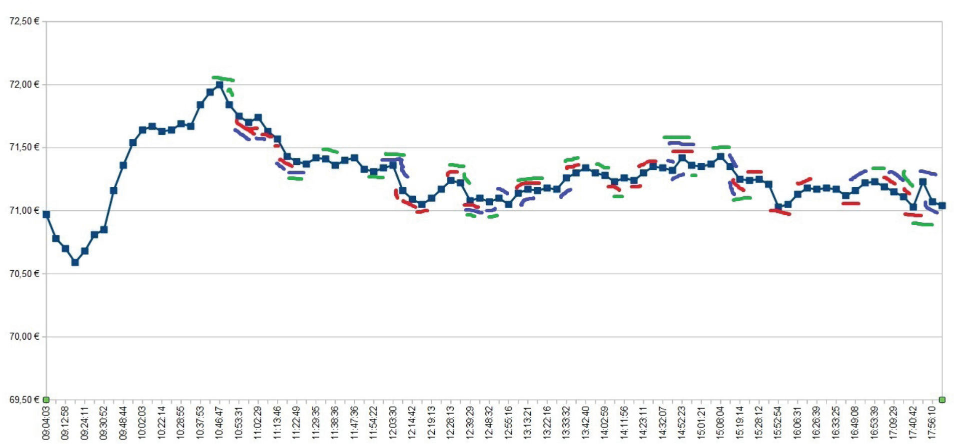


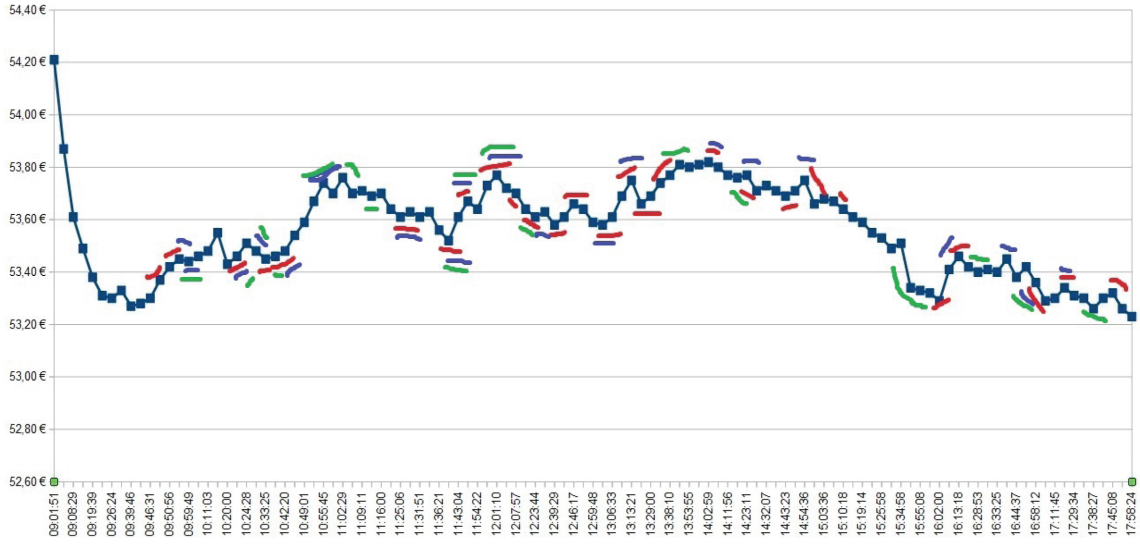
Figure 7 shows a corresponding picture as Figure 6 for the Allianz share. In the rear area, both lines recognize the various turning points quite reliably. However, it should be noted that the overall unsteady course with rapid changes must indicate a correspondingly large number of results, does not allow a clear conclusion in the middle area with regard to the turning points, and in this respect, should not be used to check the plausibility of the results.

Figure 8. BASF share price development on April 1, 2021, change points



This looks equally interesting for the BASF share in Figure 8. Here, the 1_8 line was also used (blue). 2_8 and 2_10, with the exception of the end of the day at about 17:50, clearly show the performance from about 10:30, but the trend is only minimally upward. 1_8 comes at the end again in its display to a short rise and directly afterwards to a fall of the value.

Figure 9. Bayer share price development on April 1, 2021, change points



When looking at the Bayer share price development in Figure 9, the previous results can be confirmed. With the lines 2_8 and 2_10, meaningful turning points are recognizable. (Trajectories of other stocks such as BMW, GEA, etc. are therefore not shown here.)

Need for Adjustment

Accordingly, the run on April 1, 2021, clearly shows that adjustments to the program run are necessary. In addition, it can be seen that other step definitions, such as 1_8 and 2_5, also need to be reviewed. Accordingly, a run was performed on April 7, 2021, using the various definitions. This presented the following results.

Figure 10. Adidas share price development on April 7, 2021, change points

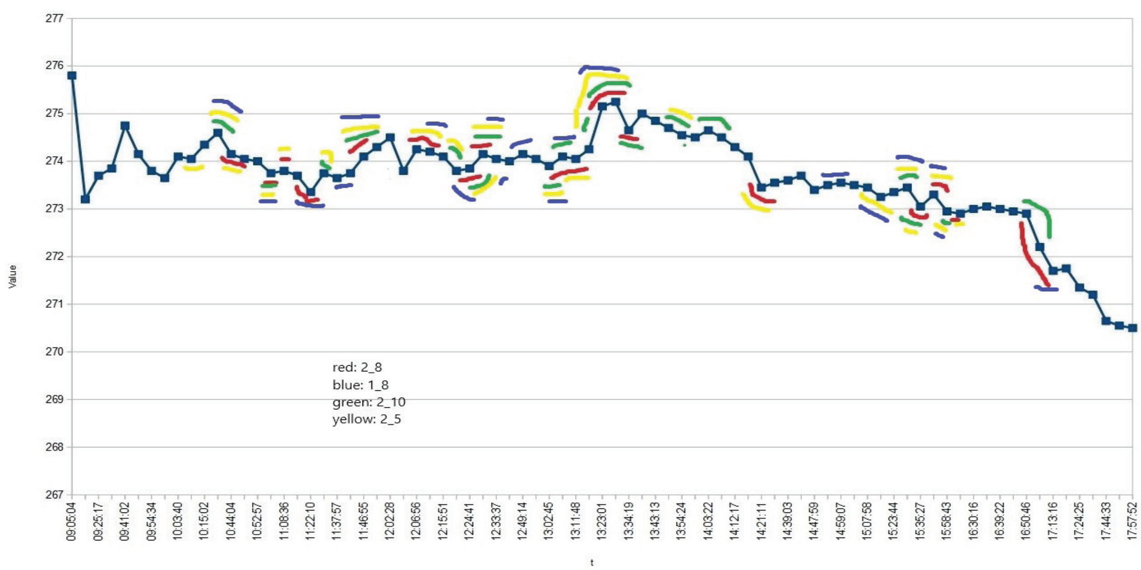
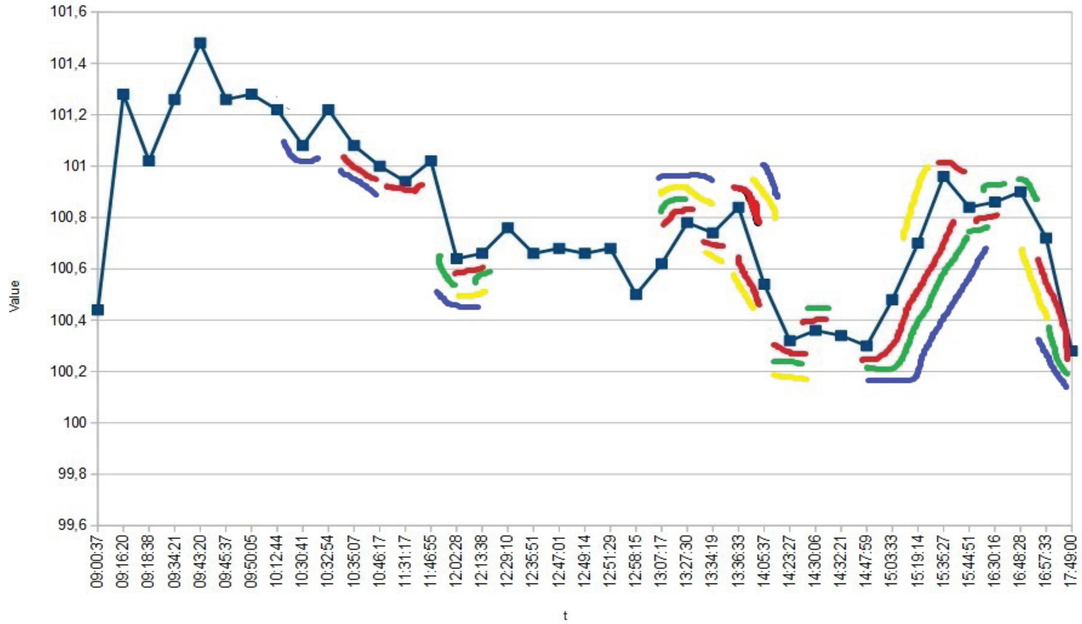


Figure 10 clearly shows that the 2_8 definition (red) achieves reliable results as long as the rate is unambiguous. Rapidly successive price changes, as in Figure 7, can also be detected here between 10:30 and 13:10. On the one hand, they are reliably displayed, but they are not optimal as a trend display. Only with decreasing values from approximately 14:00 and especially with 2_8 around 16:50 to 17:15, unambiguity arises.

Figure 11. Airbus price trend on April 7, 2021, change points



As shown in Figure 11, the Airbus change line of April 7, 2021, from about 13:30 onwards, consistently correctly shows the turning points both in the strongly rising and subsequently falling phase with certainty. Gaps are to be identified beside the phase to 10:15 as initially not recognized phase in particular at the time points 10:30 and 11:45.

Figure 12. Allianz price trend on April 4, 2021, change points

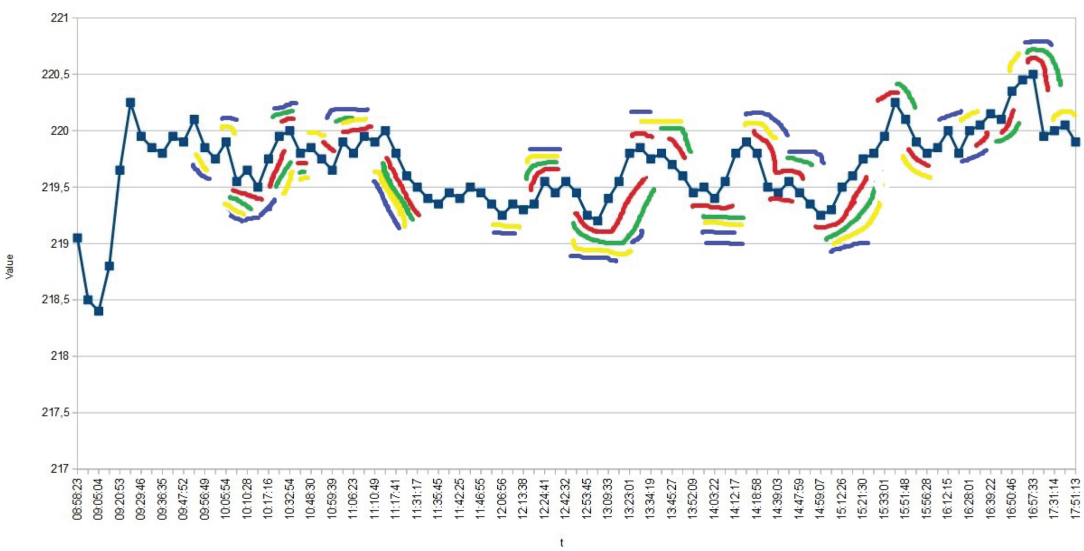


Figure 12 shows a reliable recognition of all phases of the decline and the fall by the lines. The exceptions here are also the initial phase until about 10:00 and the slight rise at about 11:45, which, however, also does not seem to be clear enough. The 2_8 definition is also the clearest here. The 2_5 definition advances to an equally good auxiliary line as the 2_10 before.

Figure 13. BASF share price development on April 7, 2021, change points

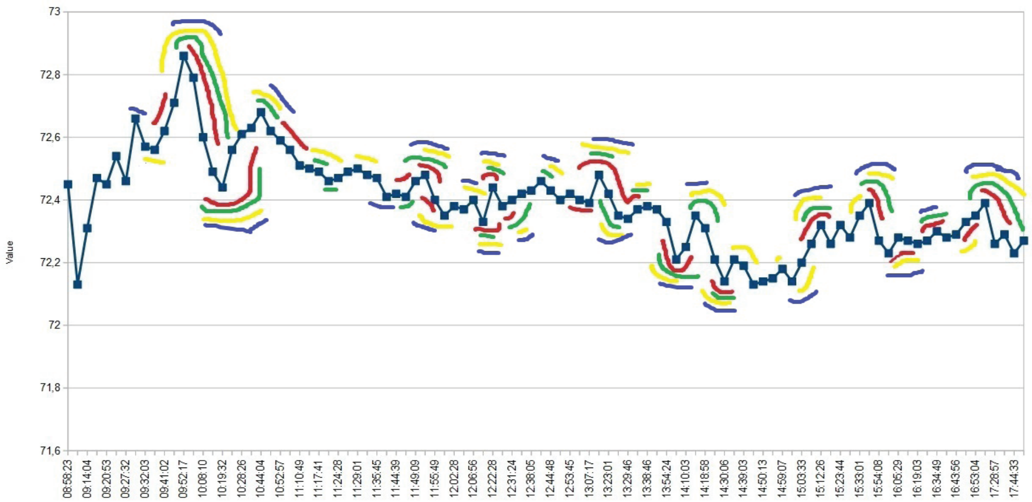
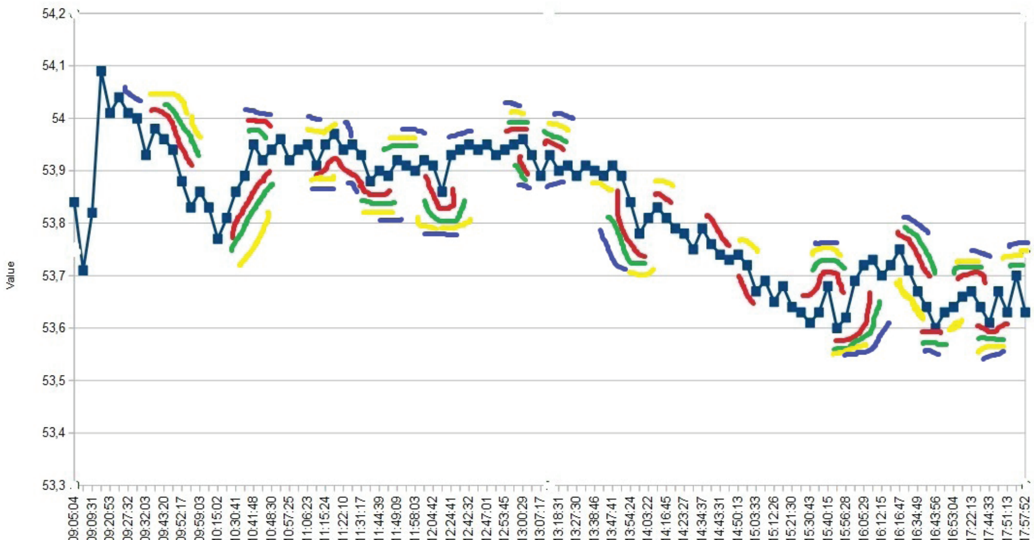


Figure 14. Bayer share price development on April 7, 2021, change points



In fact, Figures 13 and 14 are analogous to Figure 12. Clearly, the turning points with the definitions 2_8, 2_5, and also 1_8 are very well recognized. Thus, there is only a need for adjustment in the front area until about 10:00. Here, the recognition quality is not given.

Adaptation Requirement

Accordingly, the run on April 7, 2021, shows that further adjustments of the program flow are necessary, especially in the front area of the curve generation. Additionally, it can be seen that the step definitions 1_8 and 2_5 need further verification.

The source code was adapted in procedure TForm1.Fibo1. As long as there are no left outer values after F-Step, the first generated value is used as the outer value.

Table 5. Excerpt source code definition of the two trend outer values after adjustment

```
[...]
  i:=StringGridValues.RowCount;   k:=0;
[...]
  if (i > 0) then
   begin
    for t:=i-1 downto 1 do
     begin
      if ((TRIM(StringGridValues.Cells[4,t]) = ‘x’)) then
       begin
        k:=k+1;               // Counter for relevant Values
        if (k = fstep0) then  // Edit of right Value, mostly 2
          begin
           wrechts:=StringGridValues.Cells[3,t]; // right Value
          end;
```

```
        if (k = fstep1+fstep0) then  // when k = right Value + left Value, then
          begin    // 8 as default, left and right Value can be changed between 2 and 100
           wlinks:=StringGridValues.Cells[3,t];
           countnotleft:=false;  // if enough Values, don't use first Value. Otherwise real one
          end;
       end;
      if ((length(wlinks)<2) and (countnotleft = true)) then wlinks:=ersterwert;
[...]

and

[…]
procedure TForm1.SGFill;
var
 da1: String;
 uh1: String;
 na1: String;
 ku1: String;
 rc: integer;
begin
 da1:=LabelDate1.Caption;
 uh1:=LabelTime1.Caption;
 na1:=ComboBoxStock.Text;
 ku1:=LabelNewValue.Caption;
 rc:=StringGridValues.RowCount-1;
 StringGridValues.RowCount:=StringGridValues.RowCount+1;
  StringGridValues.Cells[0,rc]:=da1;
  StringGridValues.Cells[1,rc]:=uh1;
  StringGridValues.Cells[2,rc]:=TRIM(na1);
  StringGridValues.Cells[3,rc]:=ku1;
  StringGridValues.Cells[4,rc]:='_';
  if ((length(LabelW1.Caption)>0)) then
  begin
    if (LabelNewValue.Caption <> letzterwert) then
     begin
      StringGridValues.Cells[4,rc]:='x';
      if (ersterwert = '0') then ersterwert:=LabelNewValue.Caption; // '0'=default, store value
     end;   // in variable ersterwert
   end;
end;
```

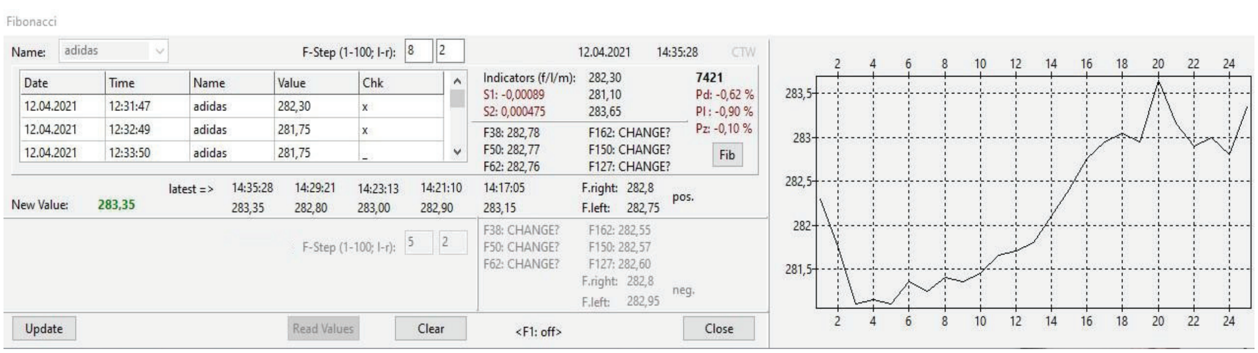
Result Verification

On April 12, 2021, another half-day only run was performed for the detail view with different definitions. This one presented the results conveyed in Figure 15a-m..

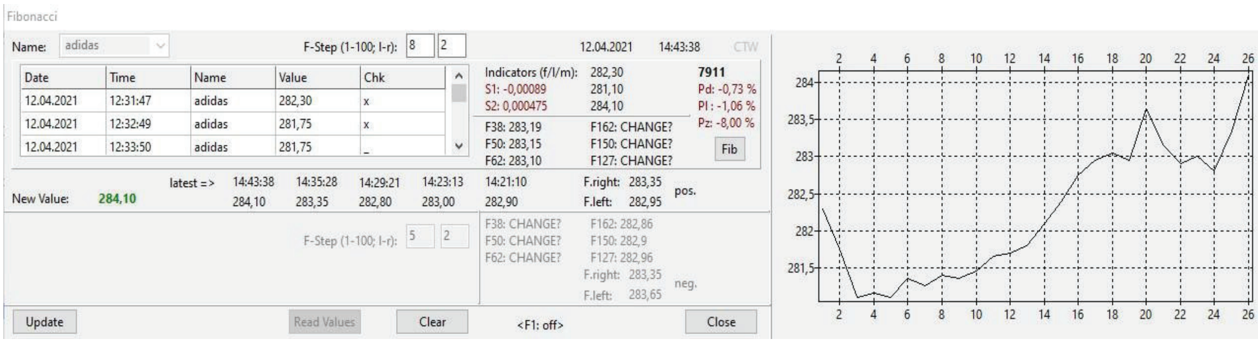
To first show the previous results again in a single case view, the time period between 14:36 to 16:46 is chosen for April 12, 2021, which presents the results sequentially. The right outer edge is relevant here.

Figure 15a-m. Sequential representation of an example development of the Adidas share on April 12, 2021

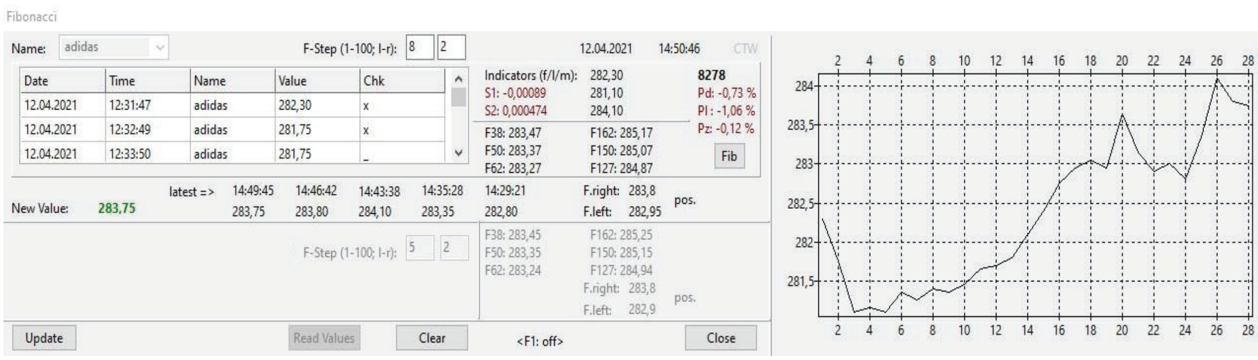
a. 14:36, indicated a strong phase.



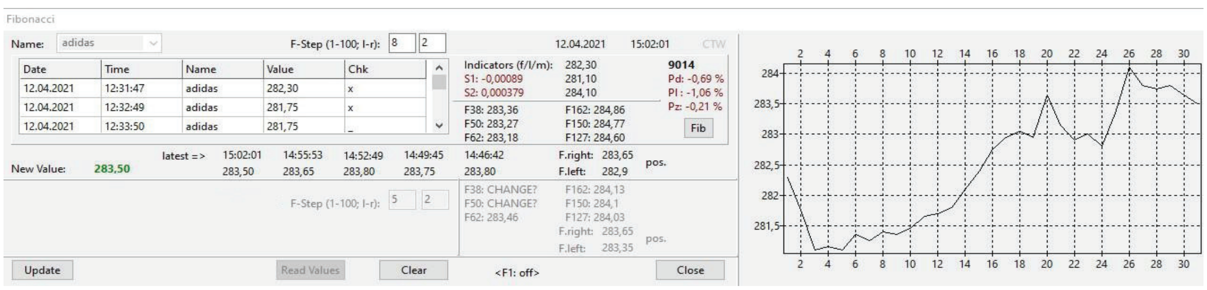
b. 14:44, 2_8 Change and 2_5 Change (each with different sides) indicate an intermediate upswing and stronger upswing phase, and possible start of the head phase of a shoulder-head-shoulder formation. Here is possibly a good position to sell.



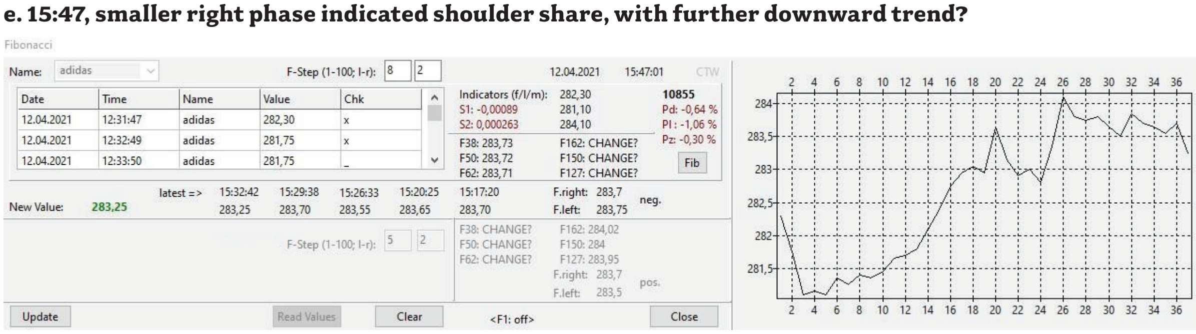
c. 14:51



d. 15:03, indicated a downturn phase.

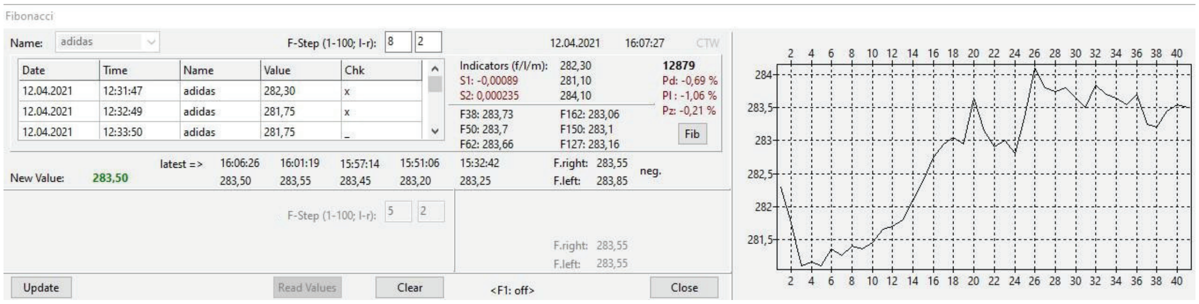


e. 15:47, smaller right phase indicated shoulder share, with further downward trend?

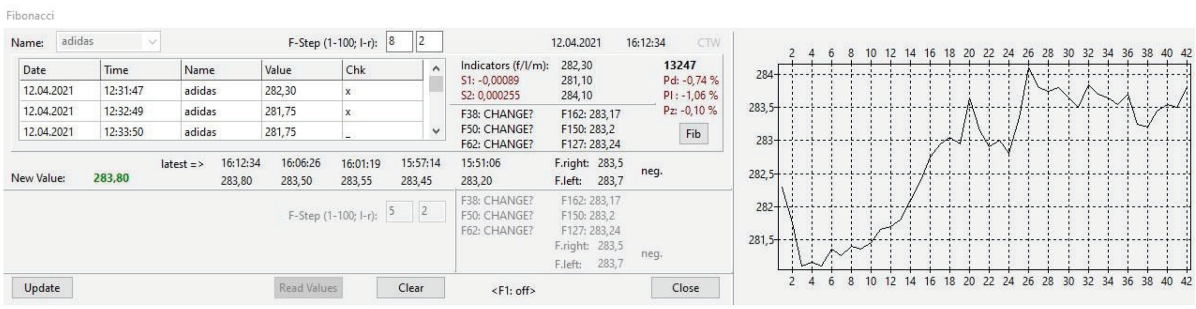


f. 15:57, no, slight upward trend again is shown in both lines.

g. 16:08, range of the lower step definition identical, therefore no display at 2_5.

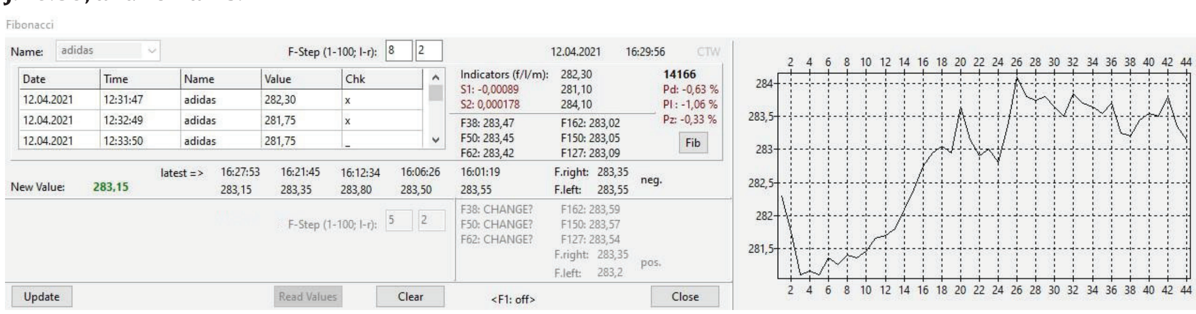


h. 16:13, rise of the price, which is also displayed as a change. Start of the subsequent high?

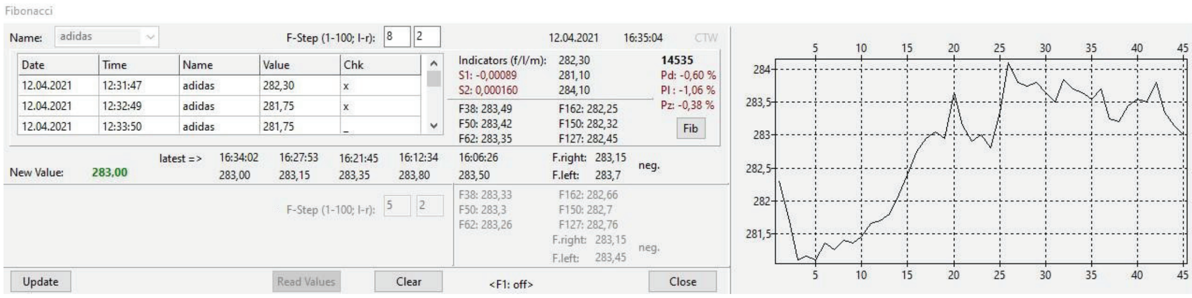


i. 16:23, no, trend is downwards.

j. 16:30, and remains.

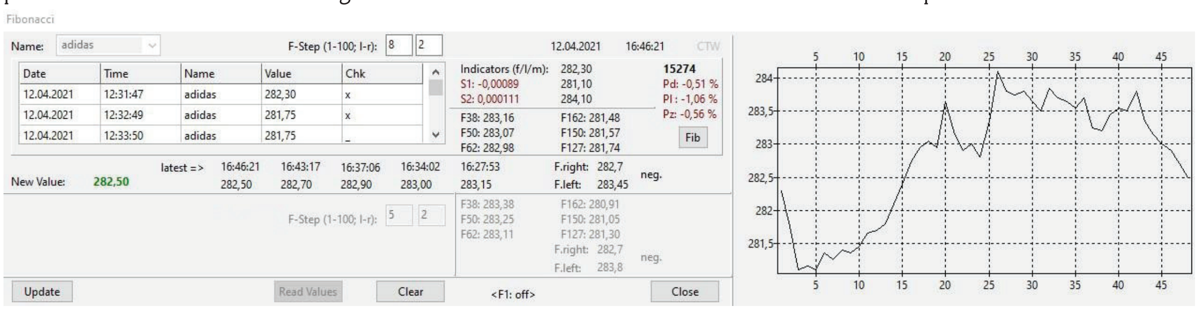


k. 16:36, as before, no turning point display, while further decreasing.



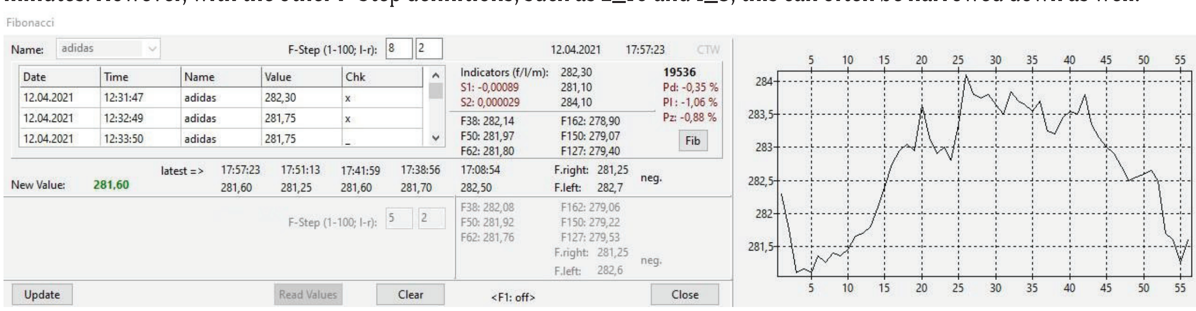
l. 16:46, continuously decreasing.

Up to this point, all switches were also displayed as a possibility of switching. The high phases could have been used as selling times, provided that the shares were bought at a time with a lower value. The difference in this example is 3.00 EUR.



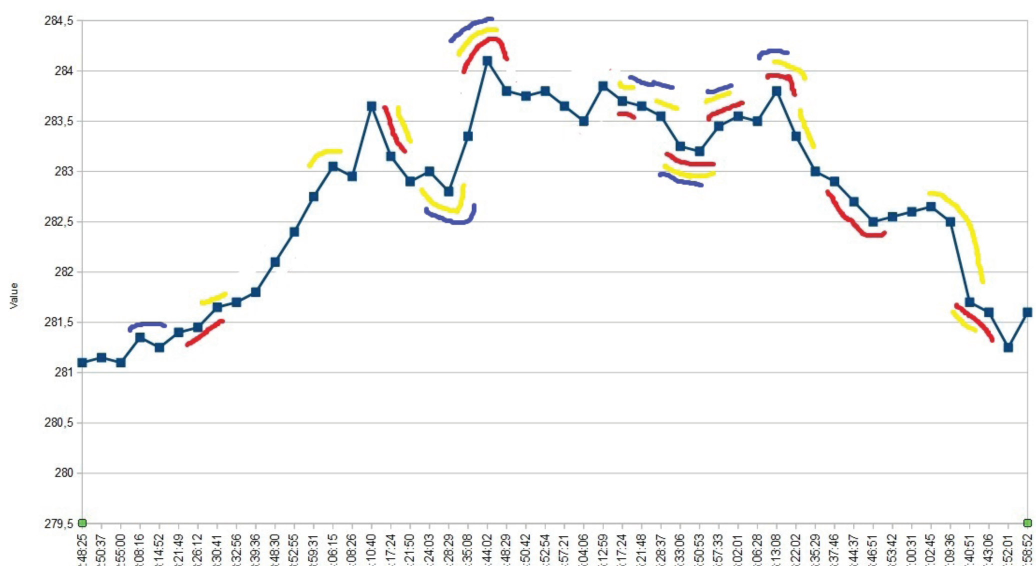
m. 17:57, low phase not displayed.

However, the last low phase at 17:57 is not shown. This corresponds to the expected error pattern for the first morning and last evening minutes. However, with the other F-Step definitions, such as 2_10 and 1_8, this can often be narrowed down as well.



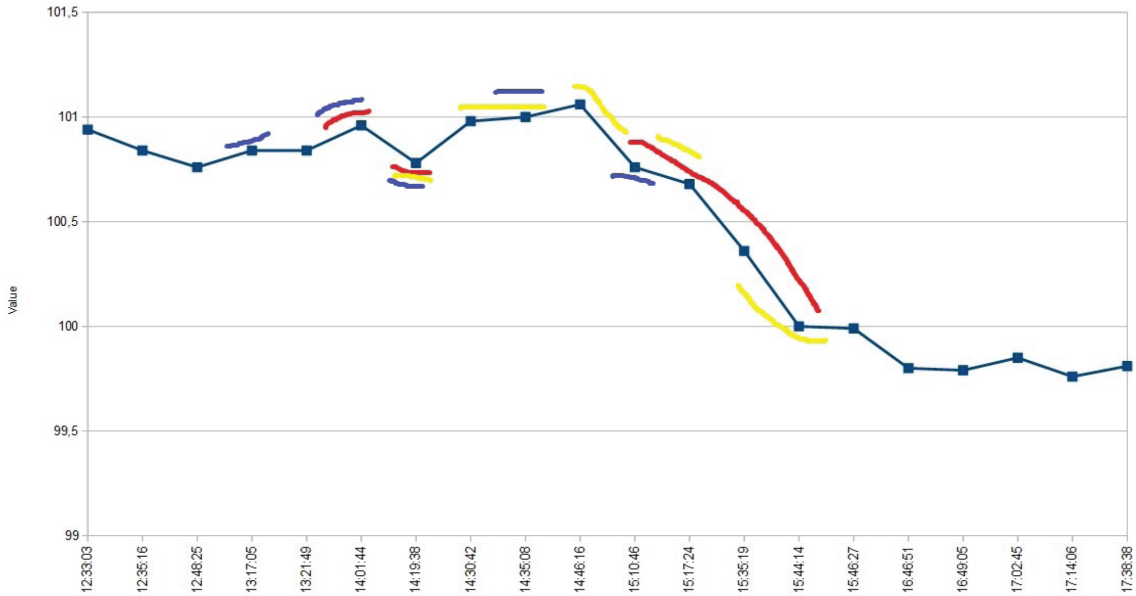
Finally, the following graphs represent the day of April 12, 2021, as of 12:30 am.

Figure 16. Adidas price trend on April 12, 2021, change points



2_8 (red) and 2_5 (yellow) are largely recognized reliably, but the rise is not recognized in the start phase, which can also result from the late start at 12:30 pm. The other phases are also recognized sufficiently, but 1_8 (blue) is insufficient.

Figure 17. Airbus share price development on April 12, 2021, change points



A corresponding picture also emerges in Figure 17 for the Airbus share. 2_8 and 2_5 serve well as F-step definitions.

Figure 18. Allianz share price development on April 12, 2021, change points

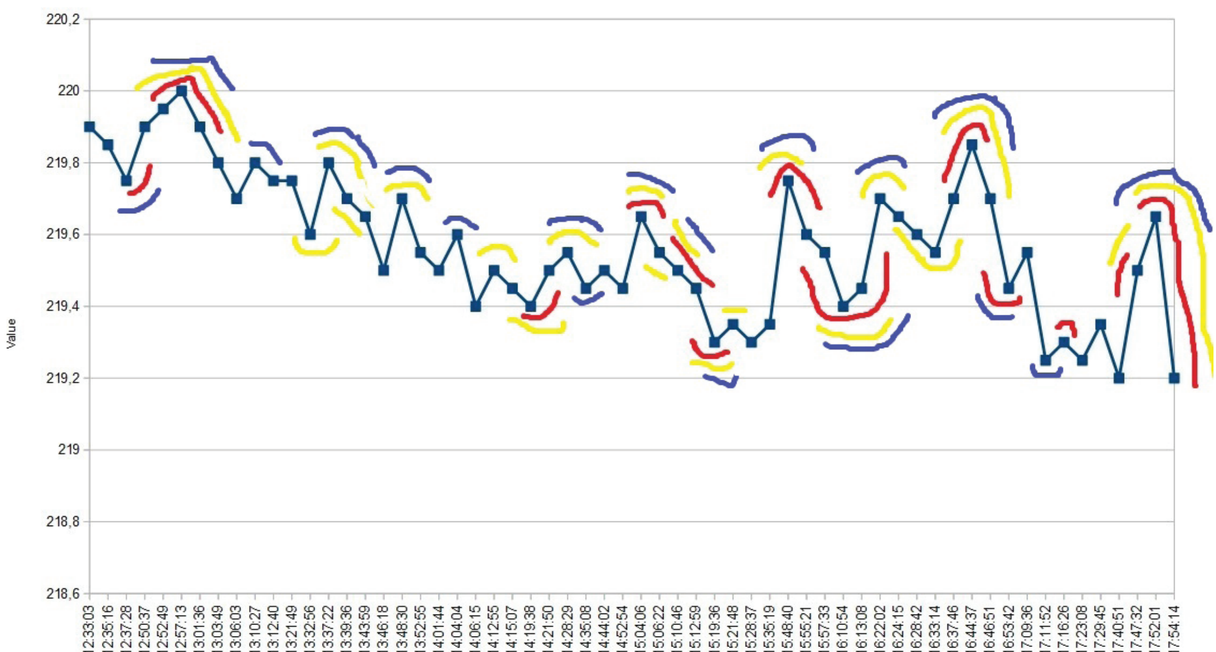
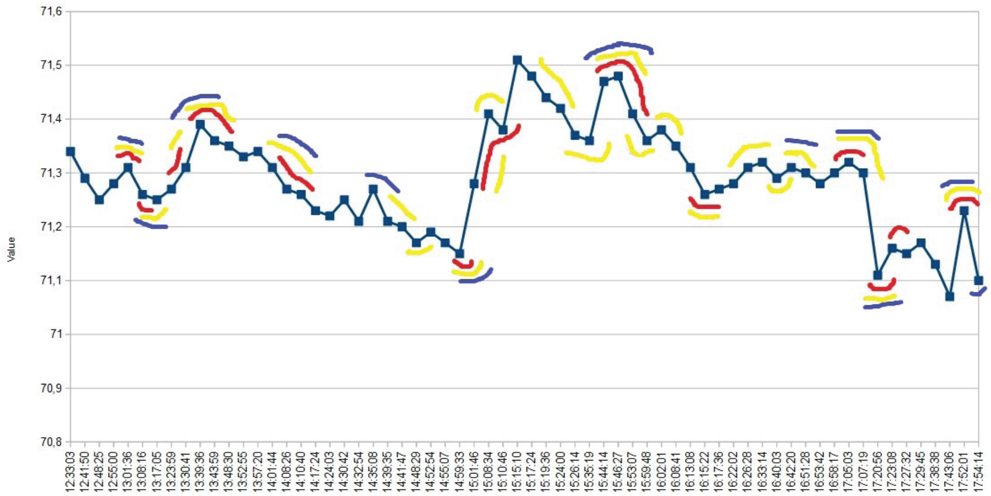


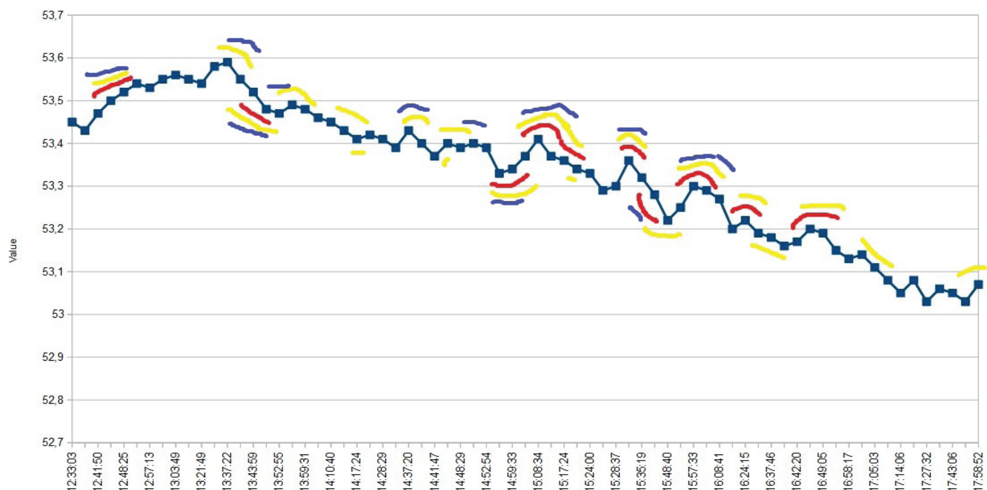
Figure 18 shows, however, that the definition of 1_8 as a supplementary line is also possible and provides solid results at certain points in time.

Figure 19. BASF share price development on April 12, 2021, change points



However, Figure 19 clearly highlights again the definitions 2_8 and 2_5 as common indicators.

Figure 20. Bayer share price development on April 12, 2021, change points



Finally, Figure 20 confirms the previously favored combination of 2_8 and 2_5.

The inclusion of the special case of the F-step definition 1_3 of April 14, 2021, shows that a shorter step definition does not lead to any significant improvements of the expected course.

Figure 21. Adidas share price development on April 14, 2021, change points 1_3

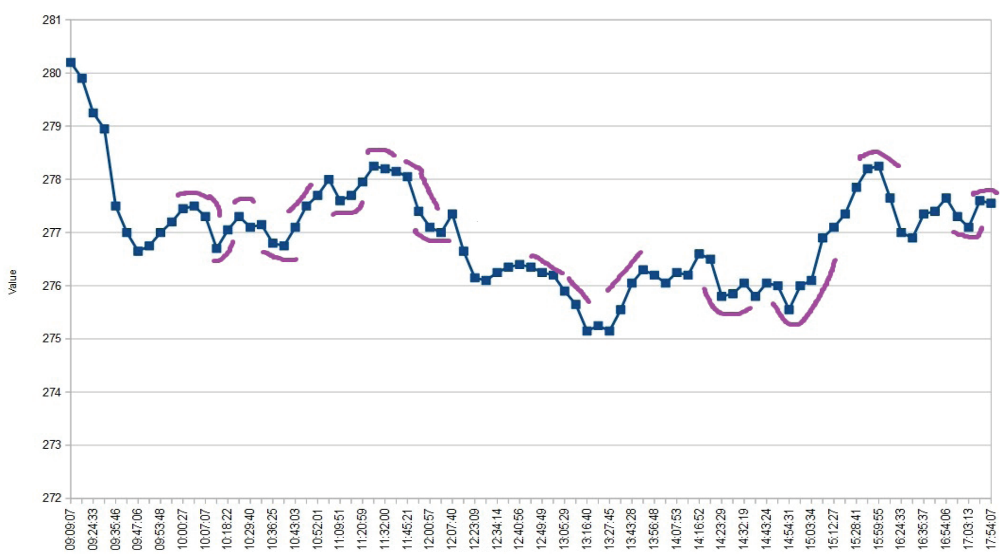
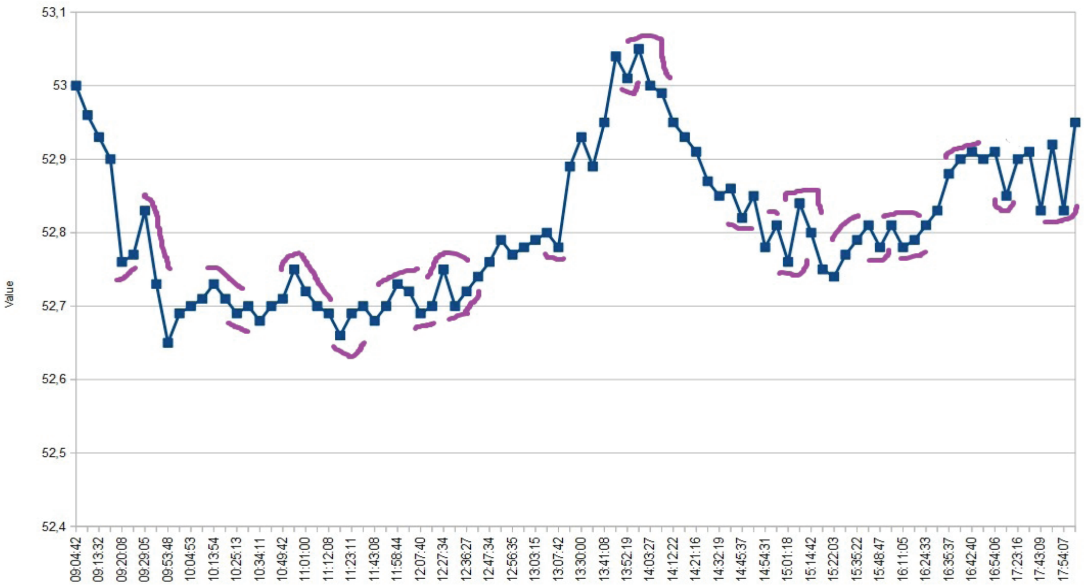


Figure 22. Bayer share price on April 14, 2021, change points 1_3



There are too many gaps in the observations here with 1_3 (purple), so that 1_3 appears unsuitable as an auxiliary line.

Consequences of Data Analysis

The previous explanations have proven that:

- The data basis for the empirical demonstration of the thesis that the present program can display the turning points of the price trend is solid.
- The display of the turning points is timely, and a high percentage of the time is correctly displayed.
- The F-step definitions 2_8 and 2_5 are suitable to provide a solid support.
- The provided DLL as integrable program resources under Windows is able to call the form calculation functionality in already existing applications.

Implementation Procedure/Special Features

The implementation was carried out in an agile manner (i.e., initially, it was exclusively tested as to whether stock prices can be read and displayed at all from https://www.finanzen.net). This is done using the following constructs:

Table 6. Reading and decomposing the price value from the internet page

```
[...]
// link check
  url:=‘https://www.finanzen.net/aktien/‘+EditNameStock.Text+‘-aktie‘; // url
  LabelUrl.Caption:=url;
  LabelUrl.Refresh;
  if ((url <> q1)) then  // if url changed
   begin
    // Variables and Labels must be empty
    q1:=url;
   end;
  httpclient := TFPHttpClient.Create(Nil); // Create; Get from *
  html := httpclient.Get(url);                              // Get; Get from *
  httpclient.Free;                                                   // Free; Get from *
  MemoHTMLText.Text := html;  // Memotext filled with html-Code; Get from *
  MemoHTMLText.Refresh;
  SuchStart := 0;
 SuchStart := FindInMemo(MemoHTMLText, ‘Aktueller Kurs:’, SuchStart + 1); // Get from *
  if (SuchStart > 0) then
    LabelTextPosition.Caption := ‘Found at Position Memo1.SelStart[‘+IntToStr(SuchStart)+’] !’
  else
    LabelTextPosition.Caption := ‘No Position found!’;
  LabelTextPosition.Refresh;
  LabelNewValue.Caption:=copy(MemoHTMLText.Text, SuchStart+15 , 12); // String with 12 chars
  Wertzerlegen(LabelNewValue.Caption);
  LabelNewValue.Refresh;
  Wertesetzen;
```

```
  SGFill;
[…]
  letzterwert:=LabelNewValue.Caption;
* [see Lazarus-TMemo]
```

Twelve characters are read each time, these are then divided using the Value Decomposition procedure, and the value without text components is determined.

Table 7. Determining value without text components

```
procedure TForm1.Wertzerlegen(S: String);
const
  ErlZeichen: Array[1..11] of String = (‘0’, ‘1’, ‘2’, ‘3’, ‘4’, ‘5’, ‘6’, ‘7’, ‘8’, ‘9’, ‘,’);
[...]
  z:=Length(S);
  if (z > 0) then
  begin
   for i:=1 to z do
    begin
     v:=copy(S, i, 1);
     // compare v in ErlZeichen
     q:=AnsiMatchStr(v, ErlZeichen);
     if (q = true) then
      begin
       t:=t+v;
       q:=false;
      end;
    end;
  end;
if (length(t)=0) then t:=letzterwert;
LabelNewValue.Caption:=t;
LabelNewValue.Refresh;
end;
```

Test Environment

In addition, a test program was developed, which is methodically the same as the main application, but which can read the values for several stock prices in quick succession. This is controlled by the variable tglob, which serves as an index for variables like „Aktienname: Array[1..10] of String;“ (arbitrarily expandable) and can then be addressed as Aktienname[tglob] (stock name).

Table 8. Adjustment of the table fill via array with tglob

```
[...]
  for t:=1 to alleaktien do
    begin
      tglob:=t;
      url:=‘https://www.finanzen.net/aktien/‘+Aktienname[t]+‘-aktie‘;    // url wird gebildet
[...]
      httpclient := TFPHttpClient.Create(Nil); // Get from *
      html := httpclient.Get(url);                         // Get from *
      httpclient.Free;                                             // Get from *
      MemoHTMLText.Text := html;                 // Get from *
      MemoHTMLText.Refresh;
      SuchStart := 0;
      SuchStart := FindInMemo(MemoHTMLText, ‘Aktueller Kurs:’, SuchStart + 1); // Get from *
      if (SuchStart > 0) then
        LabelTextPosition.Caption := ‘Found at Memo1.SelStart[‘+IntToStr(SuchStart)+’] !’
      else
        LabelTextPosition.Caption := ‘No position found!’;
     LabelTextPosition.Refresh;
     LabelNewValue.Caption:=copy(MemoHTMLText.Text, SuchStart+15 , 12);
     Wertzerlegen(LabelNewValue.Caption);
     LabelNewValue.Refresh;
[...]
     SGFill;
     BisherValue[tglob]:=LabelNewValue.Caption;
   end;
```

```
procedure TForm1.SGFill;
[...]
begin
 da1:=LabelDate1.Caption;
 uh1:=LabelTime1.Caption;
 na1:=Aktienname[tglob];
 ku1:=LabelNewValue.Caption;
 rc:=StringGridValues.RowCount-1;
 StringGridValues.RowCount:=StringGridValues.RowCount+1;
 try
  StringGridValues.Cells[0,rc]:=da1;
  StringGridValues.Cells[1,rc]:=uh1;
  StringGridValues.Cells[2,rc]:=TRIM(na1);
  StringGridValues.Cells[3,rc]:=ku1;
  StringGridValues.Cells[4,rc]:='_';
  if ((length(LabelNewValue.Caption)>0)) then
  begin
    if ((LabelNewValue.Caption <> BisherValue[tglob])) then
     begin
      StringGridValues.Cells[4,rc]:='x';  // set „x“
      if (ersterwert[tglob] = '0') then ersterwert[tglob]:=LabelNewValue.Caption;
     end;
   end;
[...]
```

Then the Fibonacci values are determined, and it is recognized whether the lines were exceeded or not. This is marked in the table in the fields provided (F38 to F162). The values are then transferred to a file at the end of the day after 18:00 and stored on the computer. This larger number of files can be evaluated to draw conclusions about further adjustments.

Gradually, over the further sprints, the adjustments were made so that finally, the program including DLL is available.

The following results are available:

- German, App, simple line definition (KursDeuSingleApp)
- German, DLL, simple line definition (KursDeuSingleDLL)
- English, App, simple line definition (KursEnglSingleApp)
- English, DLL, single line definition (KursEnglSingleDLL)
- German, App, double line definition (KursDeuDoubleApp)
- German, DLL, double line definition (KursDeuDoubleDLL)
- English, App, double line definition (KursEnglDoubleApp)
- English, DLL, double line definition (KursEnglDoubleDLL).

For verification, the test tool is provided in German and English (KursTesttoolDeu and KursTesttoolEngl). The English language versions can be found at [Wildensee (2021a+c)].

The data dumps from the test data provision are also stored in tabular form, from which the graphs of the course trajectories are then displayed and the turning points are plotted.

Figure 23. Price data dump with turning point definition (GGF. WENDE = CHANGE?)

Aktie	Uhrzeit	Kurs	Chk	F_links	F_rechts	F38	F50	F62	F127	F150	F162	F38_Wen	F50_Wen	F62_Wen	F127_Wer	F150_Wer	F162_Wer
allianz	12:26:56	219,45	x	219,45	219,35	219,41	219,4	219,38	219,22	219,2	219,18	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	12:42:32	219,55	x	219,4	219,55	219,49	219,47	219,45	219,74	219,77	219,79						
allianz	12:49:14	219,45	x	219,5	219,45	219,48	219,47	219,46	219,38	219,37	219,36						
allianz	12:53:45	219,25	x	219,45	219,55	219,51	219,5	219,48	219,67	219,7	219,71	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	13:00:29	219,2	x	219,35	219,45	219,41	219,4	219,38	219,57	219,6	219,61	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	13:11:48	219,55	x	219,35	219,2	219,29	219,27	219,25	219	218,97	218,95	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	13:23:01	219,8	x	219,3	219,4	219,36	219,35	219,33	219,52	219,55	219,56				GGF. WEND	GGF. WEND	GGF. WENDE
allianz	13:27:30	219,85	x	219,35	219,55	219,47	219,45	219,42	219,8	219,85	219,87				GGF. WENDE		
allianz	13:34:19	219,75	x	219,55	219,8	219,7	219,67	219,64	220,11	220,17	220,2						
allianz	13:38:46	219,8	x	219,45	219,85	219,69	219,65	219,6	220,35	220,45	220,49						
allianz	13:45:27	219,7	x	219,55	219,75	219,67	219,65	219,62	220	220,05	220,07						
allianz	13:47:41	219,6	x	219,45	219,8	219,66	219,62	219,58	220,24	220,32	220,36	GGF. WEND	GGF. WENDE				
allianz	13:52:09	219,45	x	219,25	219,7	219,52	219,47	219,42	220,27	220,37	220,42	GGF. WEND	GGF. WENDE				
allianz	14:01:08	219,5	x	219,2	219,6	219,44	219,4	219,35	220,1	220,2	220,24						
allianz	14:03:22	219,4	x	219,4	219,45	219,43	219,42	219,41	219,51	219,52	219,53	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	14:10:03	219,55	x	219,55	219,5	219,53	219,52	219,51	219,43	219,42	219,41	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	14:12:17	219,8	x	219,8	219,4	219,64	219,6	219,55	218,89	218,8	218,75	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	14:14:30	219,9	x	219,85	219,55	219,73	219,7	219,66	219,16	219,1	219,06	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	14:18:58	219,8	x	219,75	219,8	219,78	219,77	219,76	219,86	219,87	219,88						
allianz	14:23:27	219,5	x	219,8	219,9	219,86	219,85	219,83	220,02	220,05	220,06	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	14:39:03	219,45	x	219,7	219,8	219,76	219,75	219,73	219,92	219,95	219,96	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	14:41:17	219,55	x	219,6	219,5	219,56	219,55	219,53	219,37	219,35	219,33			GGF. WENDE			
allianz	14:54:39	219,35	x	219,5	219,55	219,53	219,52	219,51	219,61	219,62	219,63	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	14:59:07	219,25	x	219,4	219,45	219,43	219,42	219,41	219,51	219,52	219,53	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	15:07:58	219,3	x	219,55	219,35	219,47	219,45	219,42	219,09	219,05	219,02						
allianz	15:12:26	219,5	x	219,8	219,25	219,59	219,52	219,45	218,55	218,42	218,35			GGF. WENDE			
allianz	15:19:14	219,6	x	219,9	219,3	219,67	219,6	219,52	218,53	218,4	218,32			GGF. WENDE			
allianz	15:21:30	219,75	x	219,8	219,5	219,68	219,65	219,61	219,11	219,05	219,01	GGF. WEND	GGF. WEND	GGF. WENDE			
allianz	15:26:01	219,8	x	219,5	219,6	219,56	219,55	219,53	219,72	219,75	219,76				GGF. WEND	GGF. WEND	GGF. WENDE
allianz	15:33:01	219,95	x	219,45	219,75	219,63	219,6	219,56	220,13	220,2	220,23						
allianz	15:42:32	220,25	x	219,55	219,8	219,7	219,67	219,64	220,11	220,17	220,2				GGF. WEND	GGF. WEND	GGF. WENDE
allianz	15:51:48	220,1	x	219,45	219,95	219,76	219,7	219,64	220,58	220,7	220,76						
allianz	15:54:08	219,9	x	219,35	220,25	219,9	219,8	219,69	221,39	221,6	221,7	GGF. WENDE					
allianz	15:56:28	219,8	x	219,25	220,1	219,77	219,67	219,57	221,17	221,37	221,47						
allianz	16:05:29	219,85	x	219,3	219,9	219,67	219,6	219,52	220,66	220,8	220,87						

Discussion

Final Conclusion

First, we need to clarify, with an IT-technical illustration in this rather simple surrounding field, such as Lazarus, whether a fastidious solution is possible. As it shows up, the application development is fast and high performance convertible. Lazarus produces a high-quality and performance conversion that can also be made available as DLL. Such DLL can be integrated again in arbitrary environments. The updated DLL contains access to the internet side (https://www.finanzen.net) to the current collection of the share prices of selected titles. There are currently 24 different titles, mainly from Germany. The procedure is explained, and the price is queried every half minute and displayed in the table. An extension to other stocks and the change to another quote provider is possible without any problems.

In this respect, the application offers a positive view of the approach and clearly shows that professional applications can be extended without problems.

As far as the methodological approach is concerned, it must be explained that a market event cannot be forecast, but probabilities can very well be calculated that phases of rising and falling alternate. The error rate is known, and the prediction is statistically limited. Nevertheless, as shown above, support lines are an expression of exactly this probability. This has already been sufficiently demonstrated by other authors (see McLean [2005], p. 61ff). The presented approach assumes that drawing resistance and support lines to the price trend or, in particular, to the price change points, is a legitimate way to mark the probable turning points. There is no guarantee it will turn around, but the tearing of the support lines is at least a sufficiently coherent suspicion. Over time, a feeling for the correct points of time will develop. It should be noted that if the difference between the left and right limits is too small, the presentation of a possible turning point is problematic. If the difference is sufficiently large, the trend reversal can be recognized with a high hit rate of up to approximately 90%, even if this occurs with a slight time delay. Nevertheless, by centering on the change points, the trader usually has enough time for a trading reaction even if the price difference is minimal.

As it turns out, the F-Step definitions 2_8 as the main and 2_5 as the complementary correction line are well suited to present solid results on probable turning points.

As mentioned, too choppy progressions with deflections occurring in short succession are insufficient for recognition, but meaningfully sustained movements can be clearly identified. For the future, if necessary, further F-step definitions, such as 1_4, 2_4, 1_6, 2_6, should be checked with regard to their effect. In conclusion, however, a very solid result is available. In particular, it should be noted that this approach should also be investigated for the energy trading field. This trading field is especially known for volatile day trading patterns. Other stock markets are good targets for this approach, too.

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Software and Data

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Lazarus-TMemo: https://wiki.lazarus.freepascal.org/TMemo/de.

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The EMD Oscillator

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Abstract

The Empirical Mode Decomposition (EMD) and its application in technical analysis was the topic of my MFTA thesis (Reiss 2019). The results of that paper cover the adaption of the EMD to financial time series, an EMD-based price projection, the development of an EMD-based moving average, and, finally, two trend following trading systems. The research was awarded with the John Brooks Memorial Award and this honor was the incentive for me to continue this work.

In this paper, the EMD approach is now elaborated to swing trading. For the convenience of the reader, the EMD algorithm and the EMD moving average are recalled. This builds the basis to introduce the EMD Oscillator, present its computation, and the generation of buy and sell signals. Furthermore, the recommended settings for the oscillator are provided, as well as a quantitative distinction between "oversold" and "very oversold." The usage of this indicator is shown by presenting two swing trading strategies based on this new oscillator.

Introduction

Based on Charles Dow, there are three trends in the market. He illustrated the primary trend as the tide of the sea, the secondary reaction as the large waves of the sea (swell), and the daily fluctuations in the markets correspond to the ripples of the water (wind sea). Having this analogy in mind, it makes sense to apply results from hydrospheric research to technical analysis.

To eliminate the disturbing interference of sea waves from data, researchers from several hydrospheric research institutes (Huang and others 1998) developed the Empirical Mode Decomposition (EMD). A first adoption of the EMD to financial price series has been performed by Dürschner (2014), but there was still the need for further adaptions. These are presented in Reiss (2019) and, with regard to trading, that paper was focused on trend following approaches, hence investing in the primary trend. However, it did not cover how to trade the secondary reactions, and the current paper will close the gap to EMD based swing trading.

To recapitulate the EMD, a characteristic example is shown. The result is a *decomposition* of a financial time series into the basis trend and several smooth *modes* (waves) which are called Intrinsic Mode Functions (IMF). The IMFs of a decomposition are ordered. The wavelength and amplitude of the IMF are increasing with the order of the IMFs. The algorithm to obtain this decomposition is *empirical*, hence driven only by the input data without further assumptions. For the convenience of the reader, the EMD algorithm based on the previously cited results is recalled.

One application of the EMD is recalled, namely the construction of a moving average (EMDMA). The fundamental idea of any moving average is to smooth the price over a certain period. Using the EMD one can construct a moving average which erases the smaller waves in the price signal which are identified as the IMFs with a lower order.

Typically, a swing trading approach is based on overbought or oversold states of the market, indicated by an oscillator. Following the definition of the Commodity Channel Index, which is given as a scaled difference of the price and its moving average, the EMD Oscillator is defined by two steps. At first, the difference of the price and the EMDMA is computed. Secondly, this difference is rescaled by its average amplitude. This result is the EMD Oscillator which oscillates around zero and, like the Commodity Channel Index, the EMD Oscillator exceeds the values of -1 or 1, which are important trigger lines. The mathematical algorithms needed for all computations used in this paper can be found in standard literature (e.g. Press and others 1992), and the computation of the amplitude based on the Hilbert transform is explained in this paper.

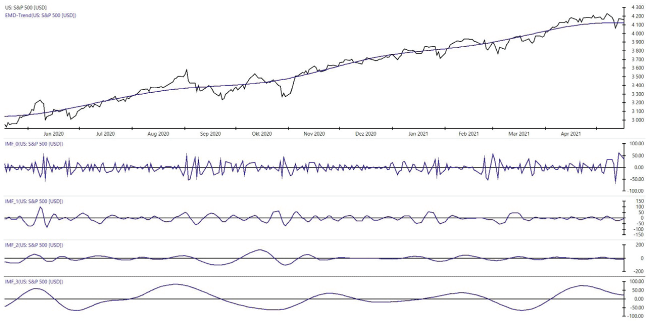
To illustrate the effectiveness of the EMD Oscillator, two swing trading strategies are presented to complete the paper. The first one is related to trade one instrument only (for example the S&P 500 Index) and highlights the distinction between "oversold" and "very oversold." The second one provides a short-term stock selection strategy, hence selecting the most auspicious stocks, e.g., from the constituent equities of the S&P 500 Index.

The Empirical Mode Decomposition

Characteristics of the EMD

Let us start with an introductive example. Figure 1 shows the EMD of the S&P 500 Index over the period of one year. In the top window, the S&P 500 is presented in black, and the blue lines represent the result of the EMD. The blue line in the top window is the *trend component* and lies in the area of the S&P 500. The windows below show the Intrinsic Mode Functions (IMF) of the decomposition. These IMF fluctuate around zero since all maxima are positive and all minima are negative. With increasing order, the IMFs become smoother, and their amplitude and their wavelength increases.

Figure 1. An example of the Empirical Mode Decomposition



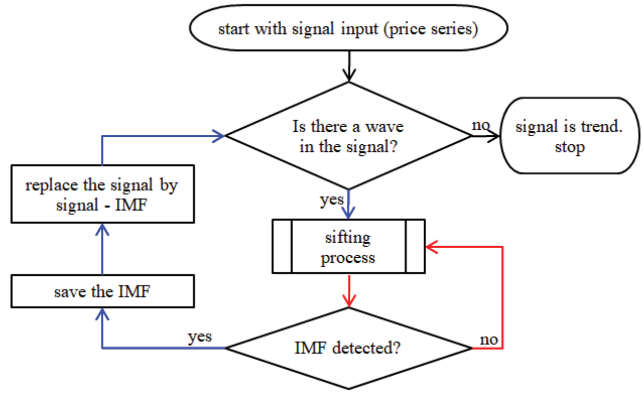
Hence, the IMFs are designed to cover non-stationary waves in the market. The wavelengths and amplitudes vary over time for each IMF. Therefore, the EMD can be regarded as a generalization of the classical cycle theory which comes clear if we recall the five principles of cycle theory and check them against the IMFs:

- **Summation:** The price movement is exactly explained by the movements of all underlying waves (IMFs) and the trend component.
- **Proportional:** Each subsequent IMF has an increased wavelength and amplitude.
- **Synchronization:** Often a high or a low of an IMF wave corresponds with a high or low of its preceding IMF, but this property does not hold strictly.
- **Constant cycle length:** The wavelength or amplitude of an IMF is not constant over time, but usually of similar order.
- **Harmonics:** The wavelength of an IMF is not an integer multiple of its preceding IMF. As a rule of thumb, it is often a factor between two and three.

EMD Algorithm

Typically, the technical analyst starts the analysis from the large timescale and refines the analysis by breaking down the time frame. The EMD works the other way around. The smallest wave is extracted at first and the next iteration identifies the smallest remaining wave, and so on until all waves have been segregated. The core algorithm is shown in the flow chart (Figure 2). The initial signal is the price series and as long as the signal includes a wave, a so-called sifting process is applied until an IMF has been isolated. The determined IMF is stored and subtracted from the input signal and this decomposition will be repeated until the remaining signal is not wavy anymore. Finally, the remaining signal gives the trend component, and the complete decomposition consists of this trend component and all identified IMFs.

Figure 2. Flow chart of the EMD algorithm



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

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

The inner loop of the algorithm, which is shown in red in the flow chart, is used to identify the next and smallest available wave from the data. This wave will be the next IMF and is segregated by multiple application of the sifting process. The stopping criteria for the iteration of the sifting process is given by Reiss (2019):

- The sifting process has been performed at least five times, and
- all local maxima of the IMF are positive, and all local minima of the IMF are negative.

Sifting Process

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

Including the additional boundary conditions introduced in Reiss (2019), the mathematical and precise definition of the sifting process is given by the following steps:

1. **Identify the upper band**
   The upper band is defined as the cubic spline with natural boundary conditions supported by all local maxima of the signal and two points at the left and right edge. Their value is given by the maximum of the signal at the edge and the nearest local maximum.

   For the definition and an algorithm to compute a cubic spline, see Press and others (1992).

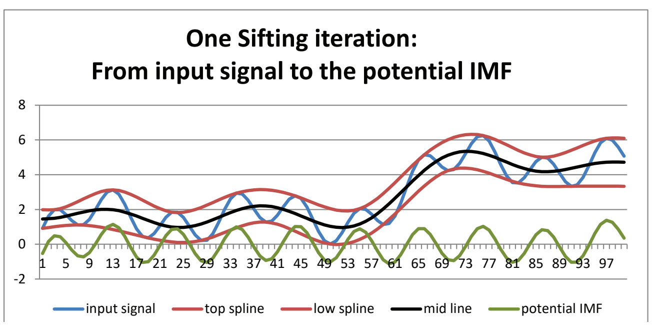
2. **Identify the lower band**
   According to the upper band, the lower band is computed as the cubic spline with natural boundary conditions supported by all local minima of the signal and two points at the left and right edge. Their value is given by the minimum of the signal at the edge and the nearest local minimum.

3. **Calculate the mid line**
   The mid line is computed as the arithmetic mean of the previously identified upper and lower band.

4. **Determine the potential IMF**
   The potential IMF is obtained as the difference of the input signal and the mid line. If the result is not an IMF or the sifting process has not been iterated at least five times, this potential IMF serves as input signal for the next sifting process.

To clarify the sifting process, the first iteration of the sifting process is shown in Figure 3 inspired by the example of Kim and Oh (2009). From the input signal (blue line), the upper and lower band are identified as cubic splines (red lines) based on the local maxima/minima of the signal and the additional points defined at the boundary. The average of both splines is the mid line (black line). The difference between the input signal (blue line) and the mid line (black line) is the result of the sifting, the potential IMF (green line).

Figure 3. Explaining one iteration of the sifting process



The EMD Moving Average

Definition of the EMDMA

Generally, a moving average is used by a technician to smooth any time series. From the characteristics of the EMD it becomes obviously clear that this task can also be performed by this technique. To remove the smaller "ripples" of the market from a time series, one can just subtract the low order IMFs. That's the definition of the EMDMA:

$$\mathrm{EMDMA}(n,t) := \mathrm{Price}(t) - \sum_{i=1}^{n} \mathrm{IMF}_i\,(t)$$

Properties of the EMDMA

For a deeper understanding of the EMDMA, Figure 4 shows the S&P 500, the corresponding EMDMA(6), and the classical simple moving average of 200 days. The parameter value of six for the EMDMA has been chosen to let the EMDMA swing in a similar fashion as the simple moving average.

Figure 4. The S&P 500, the corresponding EMDMA(6), and the standard SMA(200)

One simply identifies two important differences between the two moving averages:
1. In periods of a strong upward trend, the price is located above the SMA while the EMDMA is always located in the area of the price action—even in trending phases. That is clear from the definition, since the EMDMA is the price minus some IMFs which fluctuate around zero by definition.
2. After a correction, the EMDMA usually turns faster from being falling to rising than the SMA. This point inspired Dürschner (2014) for a simple interpretation of the EMDMA. A rising EMDMA is a long signal. A falling EMDMA is a short signal. A trading strategy and its backtest based on this idea is analyzed in Reiss (2019).

The EMD Oscillator

Motivation and Definition

The EMD Oscillator is inspired by the well-known Commodity Channel Index (Lambert 1980) which is defined by:

$$CCI = \frac{1}{0.015\,MD}\,(Price - MA)$$

In this formula, MA is the moving average of the price and MD denotes the absolute mean derivation of the price with respect to its simple moving average. Traditionally, price denotes the typical price which is given by the average of the high, low, and close quote. Of course, the CCI could also be computed on close quotes only and can be summarized as scaled difference between the price and the moving average.

This summary also holds for the EMD Oscillator; but now—as one might expect—the moving average is given by the EMDMA and the scaling will be adopted to the techniques used in the context of the empirical mode decomposition:

$$\mathrm{EMDOSC}(n,m,t) := \frac{1}{A(m,n,t)}(\mathrm{Price}(t) - EMDMA(n,t))$$

Using the definition of the EMDMA, this can be simplified to

$$\mathrm{EMDOSC}(n,m,t) := \frac{1}{A(m,n,t)}\sum_{i=1}^{n} IMF_i(t)$$

and the scaling is given by $A(m, n, t)$, the average over m periods of the amplitude of $\sum_{i=1}^{n} IMF_i(t)$. The computation of this amplitude will be presented in a later section.

Even if the EMDOSC is defined similar to the CCI, there is one essential difference. Lambert designed the CCI originally as a trend following index: buy if the index is over 100 and exit if it falls below 100. This approach is based on the idea that in a strong upward trend the price is far above its moving average. Nowadays, the CCI is also often interpreted as an oscillator: a market is oversold if the CCI is below -100 and overbought if the CCI is above 100.

Since the EMDMA stays always in the area of the price action as discussed before, the EMD Oscillator can only be interpreted as oscillator. Due to its scaling based on the average amplitude, the typical range of the oscillator is between -1.0 and 1.0, but it will exceed this range regularly. If the EMDOSC is less than -1.0, the market is oversold, and if the EMDOSC is larger than 1.0, it is overbought. Furthermore, the EMD Oscillator also provides a quantitative measure to state a "very" oversold (overbought) market condition if the EMDOSC is below -2 (above 2).

Parametrization

As explained, the EMD Oscillator cannot be used for trend following and is hence designed to support swing trading. Prior to trading, we have to care about its parametrization, hence the number of IMFs to consider. In this respect, there is a conflict of two objectives:

- The larger the number of IMFs used, the larger is the wave to surf, hence a larger n should be considered.
- The smaller the number of IMFs used, the shorter is the holding period yielding to more trading opportunities, hence a smaller n should be considered.

For a successful trading, other aspects also need to be considered. At first, a too volatile trading might be too expensive. Secondly, economic research has shown that due to psychological effects of the market participants, the price movements are mean-reverting in shorter timeframes, but surveys of longer periods also show that the price action is trendy. Usually, trend following techniques start to work out if a horizon of six months or more is considered. For very long time frames (roughly starting at three years), markets often behave mean-reverting again, that is related to business cycles and the long-term consideration of fundamentals (value-investing).

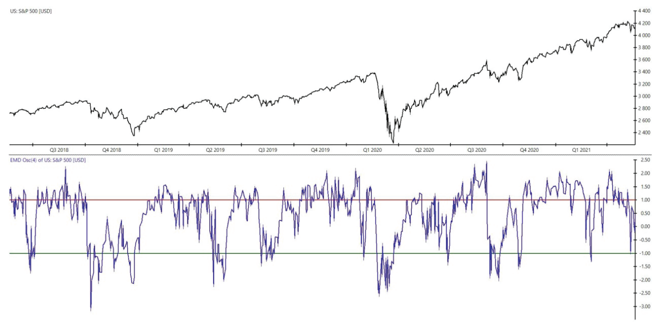
After considering all these facts, the idea is to take a larger number of IMFs, but the wavelength of the largest IMF to consider should be clearly less than six months. Therefore, the standard parameter for the number of intrinsic mode functions used for the EMD Oscillator on daily data is given by four (n=4).

Since the EMD is designed to detect non-stationary waves, the amplitudes of the IMF vary in time. For the computation of the EMDOSC, the parameter m needs to be fixed: the number of days used to compute the average of the amplitude. To facilitate the computations, m should be a power of two, and to match to the larger waves, the period to average the amplitude should be larger than a month. For that reason, the default choice is m=32.

Throughout this paper, only this default setting (n=4 and m=32) is used. Each empirical mode decomposition is performed on a moving time window based on a 3-year horizon.

Trading Signals

Figure 5. The S&P 500 and the corresponding EMDOSC(4,32) with the -1 and +1 threshold



To get an impression of the EMD Oscillator, an example is shown in Figure 5. The underlying in this example is the S&P 500 Index. The indicator oscillates around 0 and exceeds the values of -1 (oversold area) and 1 (overbought area). In rare cases, the absolute value of the EMD Oscillator exceeds 2—in this case one can define the market as "very overbought" or "very oversold." Oscillator values far below -1 are especially easy to understand: The amplitude which defines the scaling of the oscillator is obtained by an average of 32 days. During an intensive downturn the volatility in the markets often increases and hence the scaling needs some time to catch up.

Keeping the market wisdom "overbought does not mean it's over" in mind, the signals are not generated by entering the overbought or oversold area, but by leaving them. A buy signal is triggered when the oscillator crossed the -1 level from below and a sell signal is triggered if the oscillator crossed the 1 from above. To analyze, if this approach is effective, a trading system based on this simple rule is presented below.

Computation of the Amplitude Using the Hilbert Transform

The Amplitude of Oscillations Centered at Zero

The Hilbert transform is a linear transformation which provides for a given oscillation, another oscillation with the same amplitude, and the output is orthogonal to the input. Simple closed form examples are:

$$\mathcal{H}\{\cos(\omega\ t)\} = \sin\ (\omega\ t)$$

$$\mathcal{H}\{\sin(\omega\ t)\} = -\cos\ (\omega\ t)$$

$$\mathcal{H}\{1\} = 0$$

Let $X(t)$ be an oscillation centered at 0 and define $Y(t) := H\{X(t)\}$, then the amplitude A(t) is given by:

$$A(t) = \sqrt{X(t)^2 + Y(t)^2}$$

Example: Let $X(t)=\cos(\omega\ t)$, hence $Y(t)=\sin(\omega\ t)$ and the amplitude of $\cos(\omega\ t)$ is 1 as expected, since:

$$A(t) = \sqrt{\cos(\omega\ t)^2 + \sin(\omega\ t)^2} = 1$$

The Scaling of the EMD Oscillator

In the case of the EMD Oscillator, the input $X(t)$ is an oscillation centered at zero by definition.

$$X(t) = \sum_{i=1}^{n} IMF_i(t)$$

and let $Y(t) := H\{X(t)\}$ be its Hilbert transform. This computation is usually based on the last m data points of X denoted by X_i and the result of the Hilbert transform. Y also has m data points Y_i. The amplitude used for scaling the EMD Oscillator is given by:

$$A = \frac{1}{m} \sum_{i=1}^{m} \sqrt{X_i^2 + Y_i^2}$$

The Amplitude of Non-Centered Oscillations

To complete the discussion, and as a warning remark, one should note that the property of an oscillation to be centered at zero is necessary. So let $X(t)=1+\cos(\omega\, t)$ then its Hilbert transform is given by
$Y(t) := H\{1+\cos(\omega\, t)\} = H\{1\} + H\{\cos(\omega\, t)\} = \sin(\omega\, t)$

and $\sqrt{X(t)^2 + Y(t)^2}$ does not yield to the correct amplitude of one.

In such situations, the Hilbert transform needs to be applied twice to obtain the amplitude of $X(t)$:

$$Y(t) := \mathcal{H}\{X(t)\}$$

$$Z(t) := \mathcal{H}\{Y(t)\}$$

$$A(t) = \sqrt{Y(t)^2 + Z(t)^2}$$

Fortunately, for the computation of the EMD Oscillator we have to compute the amplitude of a sum of IMFs which is centered at zero. Hence, there is no need to compute the Hilbert transform twice to determine the amplitude.

Numerical Computation of the Hilbert Transform

In the following definition of the Hilbert transform the integral is taken over the domain of $X(t)$ and the integral should be taken as Cauchy principal value:

$$\mathcal{H}\{X(t)\} := \frac{1}{\pi} \int \frac{X(\tau)}{t-\tau}\, d\tau$$

This integral forms a convolution which can efficiently be calculated using the Fourier transform with this convention:

$$\mathcal{F}(f)(s) = \int f(t) e^{i\,s\,t}\, dt$$

Due to the properties of the Fourier transform on convolutions for the first equality, and some integral computations for the second equality, we obtain:

$$\mathcal{F}\{\mathcal{H}\{X(t)\}\}(s) = \mathcal{F}\{X(t)\}(s) \cdot \mathcal{F}\left\{\frac{1}{\pi\, t}\right\}(s) = \mathcal{F}\{X(t)\}(s) \cdot i\,\mathrm{sign}(s)$$

This formula provides the complete guide for the computation of the Hilbert transform of $X(t)$ by utilizing the Fourier transform. For numerical applications, the Fourier transform is often calculated based on the Fast Fourier Transform (Press and others 1992), which is the reason to choose the number of data points as a power of two.

1. Compute the Fourier transform of X.
2. Multiply the result with +i for s>0, with –i for s<0, and with 0 for s=0.
3. Compute the inverse Fourier transform of the previous result to obtain $H\{X(t)\}$.

Swing Trading With the EMD Oscillator

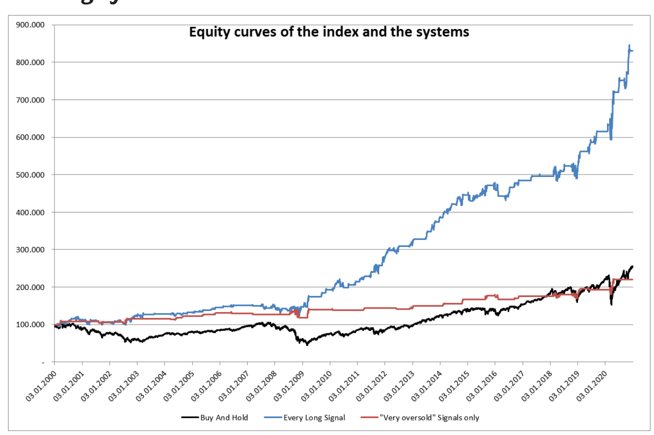
Trading the EMD Oscillator Signals on the S&P 500

As already stated, a buy signal is triggered if the EMD Oscillator crosses the level of -1 from below and a sell signal is triggered when the EMD Oscillator crosses the level of 1 from above. This simple approach is the basis for this trading system. It is just augmented with a basic risk management. Whenever a buy signal is triggered and the financial instrument is purchased, a stop loss order is established at the low of the last five days. The position is closed either on stop loss or if the EMD Oscillator triggers the sell signal.

This system is examined on the S&P 500 index from 2000 to 2020. Additionally, one could modify the system and accept only the buy signals based on a "very oversold" state. Hence, if the minimum of the current downturn of the oscillators exceeds the level of -2.

The results of these trading approaches are listed in Table 1 and the equity curves are shown in Figure 6. The initial capital for the backtest was 100,000 USD and on every entry signal the total available cash is invested. There are no transaction costs, interest, or dividend payments considered.

Figure 6. The equity curve of the S&P 500 and the two trading systems



The results show clearly that both systems have a considerable reduced drawdown than the buy and hold approach. The system, which by every signal provides enough signals to outperform the index, and the second system, which only buys the very oversold signals, has too less trading opportunities (only about two per year), so that there is no outperformance achieved even if the winning rate of this system is higher compared to the system investing at each long signal.

To utilize the higher hit rate of the second system and combine it with the first system, one could create a new system which uses the information on the state "oversold" or "very oversold" for the money management. Every long signal of the EMD Oscillator is used, the stop loss is considered at the low of the last five days, there is a full investment for the "oversold" signals, and the investment is leveraged up for the "very oversold" signals by an equally sized investment in the S&P 500 future, hence the leverage is two if the EMD Oscillator went below -2 in the current move. Due to the partial leverage, the return is drastically improved for the costs of a higher drawdown in this case, see Table 1. But even this higher drawdown is still significantly lower compared to the buy-and-hold approach.

The equity curves shown in Figure 7 confirm the effectiveness of the idea to link the minimum level of the EMD Oscillator at each downturn to the money management of the combined trading system.

Figure 7. The equity curves of S&P 500, the previous systems, and the combined system

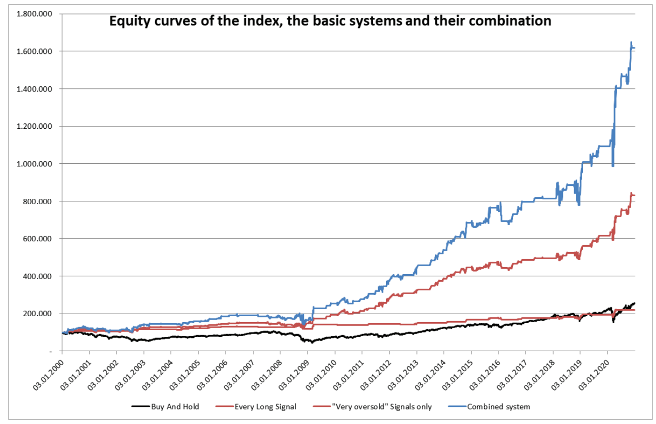


Table 1. The statistics of the systems traded on the S&P 500 index

System	Final Equity	Maximum Drawdown	Trade Count	Percentage Profitable	Average Profit Per Trade
Buy-and-Hold	256,554 USD	57.6%			
All Long Signals	829,879 USD	19.6%	169	37.9%	1.26%
Very Oversold Only	220,257 USD	15.9%	39	48.7%	2.05%
The Combined System	1,619,264 USD	30%	169	37.9%	1.66%

Buying the Most Oversold Stocks

Besides trading of a certain instrument, there is the alternative approach to select the instruments to invest in from a given set. Such selection strategies are well known and working strategies in technical analysis, e.g., investing in the stocks with highest momentum was presented in Levy (1968) and also the idea of buying the stocks with low volatility is also quite old (Haugen and Heins 1972). For this paper, a selection strategy based on the idea of purchasing the most oversold stocks based on the EMD Oscillator is introduced.

The basic idea of this system is based on the assumption that the stock price will return to its EMDMA since its level is based in the center of the price action. Remember that the following relationship holds:

$$\text{EMDMA} = \text{Price} - \text{Amplitude} * \text{EMDOSC}$$

Hence from the calculation of the EMD Oscillator, the level of the corresponding EMDMA is also known. Since the current level of the EMDMA is the price target, the expected return is given by:

$$\text{Expected Return} = -\frac{\text{Amplitude} * \text{EMDOSC}}{\text{Price}}$$

The idea is now to purchase each day the stock with the highest expected return. To be concrete, the basic set of stocks has been chosen to be the constituents of the S&P 500 and the maximum number of stocks to hold is set to 10. At each day where the number of current positions in the portfolio is less than 10, there is one position to buy if there is at least one stock which

- is not already in our portfolio, and
- which is oversold, hence EMDOSC< -1.0.

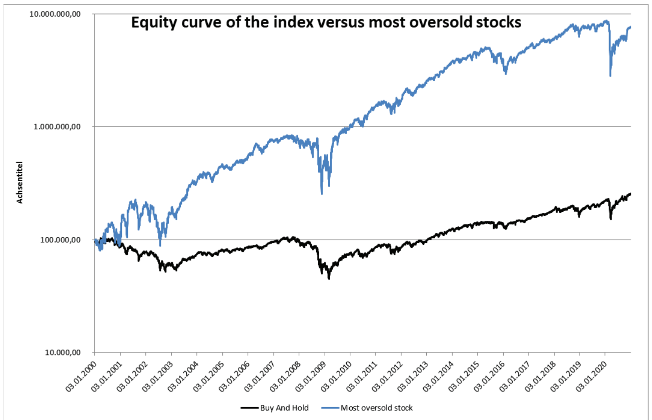
If there are several stocks which meet this condition at one day, the stock with the highest expected return is chosen. The new position is either sold at the price target (take profit order) or four weeks after the purchase date (time stop). Based on the discussion of the parametrization of the EMD Oscillator, the maximum holding period of four weeks becomes plausible.

To be honest, the following analysis of the strategy is not a stringent backtest since it is performed based on the current constituents of the S&P 500 and is therefore exposed to the survival bias. This shortcoming is consciously accepted since the purpose of this paper is rather to present the range of applications for the EMD Oscillator than to provide an optimal trading strategy.

The equity curve of this strategy is presented in Figure 8 and is starting at the beginning of 2000 with 100,000 USD raised to 7,666,244 USD at the end of 2020. The strategy turns out to be rather risky. The high performance comes at the expense of a high maximum drawdown of 70%. To complete the statistics, the share of profitable trades is about 58%.

Even if the return is clearly overestimated due to the survival bias, this trading system is presented to provide an alternative usage of the EMD Oscillator to select the most oversold stocks.

Figure 8. The equity curves of S&P 500 and the most oversold stocks system



Conclusion

In Reiss (2019), the EMD has been enhanced to utilize this method in technical analysis. The trading systems presented in that paper were designed to apply the EMD in the context of a trend-following investment approach. Since the EMD also detects the smaller waves, it was necessary and obvious to elaborate this technique for swing trading too.

The characteristics of the EMD are presented and the data driven algorithm is shortly summarized. The EMDMA is also recalled and there is one important difference to other broadly used moving averages. Even in strong trend phases, the EMDMA always stays within the area of price action. Due to this property, the EMD Oscillator, which is defined along the lines of the Commodity Channel Index, can only be interpreted as an overbought/oversold oscillator. Furthermore, also a quantitative definition of "very" overbought/oversold states can be provided because the scaling of the EMD Oscillator is based on the current amplitude of the oscillation.

The proposed default parametrization is well-suited for swing trading and is based on the fact that there is a mean reversion property in financial time series on shorter time frames. This default parametrization is also used for the backtest of two trading strategies which demonstrate the usage of the EMD Oscillator. The first strategy combines the EMD Oscillator with a stop-loss based risk management to trade one instrument only and it is also shown that the characterization of the market state as "oversold" or "very oversold" can improve the performance of the trading system, e.g., by using this information in the money management applied. It is shown that this strategy is superior to the buy-and-hold approach in terms of risk and return.

Another approach to use the EMD Oscillator is based on a "most oversold selection system" which buys each day the most oversold stock of a certain market, if any, and to limit the risk a time stop is applied. This approach ranks the stocks based on the current oscillator value and the amplitude of the unscaled oscillator. Just buy the stock with the highest expected return based on the assumption that the stock will return to its mean defined as the current level of the EMDMA.

Regardless if you prefer trend-following or swing-trading, in any case the EMD provides you the adequate tools to navigate successfully through the financial markets.

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Market Data

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

Splitting Noise and Useful Signal in the S&P 500 Members Correlation Matrix

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Abstract

Correlation matrices allow the estimating of the relationship between the price movements of different assets, something fundamental not only to estimate risks or create portfolios, but also in order to interpret technical signals in an asset historical data due to its relationship with other series and their own technical signs. In this article, a way to filter the random part out of the signal information in the correlation matrices is established by the distribution of the eigenvalues of the correlation matrix of the S&P 500 members.

Motivation

As is shown in Murphy's "Intermarket Technical Analysis...," there are important relationships between sectors and assets that a technical analyst must follow. One of the key metrics widely used is the assets' historical prices correlation matrix. Of course, this matrix is not only used in technical analysis, but in portfolio construction, both with classic and modern machine learning algorithms, risk management, and many other areas of the financial sector. This broad exposure and use of correlation between assets requires a methodology that allows removing, or at least reducing, any random element.

Random Matrices Theory (RMT)

Today, interest in large random matrices is high due to their striking practical applications. Although the beginnings of the random matrices theory (RMT) can be found in the publication of Wishart (1928), it was the work of the physicist Eugene Wigner from 1955 that made it advance due to the usefulness of certain types of matrices in the quantum mechanical investigations applications in nuclear physics. To know more about random matrices, Lal Mehta (1990) can be consulted.

As Bouchaud et al. (1999) states, "an important aspect of risk management is the estimation of the correlations between the price movements of different assets...The study of correlation (or covariance) matrices thus has a long history in finance."

For this reason, the advances in the RMT aroused interest in the financial field, and as of 1999 it took off after the publication of the first works in which the correlation of financial assets was related to the theory of random matrices by Bouchaud et al. (2000) and Amaral et al. (1999). Since those papers, many others have followed. A review of the state of the art is available at Bouchaud et al. (2017).

As it is the subject of this article, in recent years financial research has drawn attention over the need to split between the (random) noise and the informative signal that exists in correlation matrices.

Bouchaud et al. (2000) observed the results of:

- Calculating a correlation matrix of the historical prices of the S&P 500 companies.
- Studying the density of its associated eigenvalues.

They found that the bulk part of its spectral density can be associated to purely random data: "In particular, the present study raises serious doubts on the blind use of empirical correlation matrices for risk management."

Eigenvalues and Eigenvectors

The distribution of the eigenvalues in a random matrix, as the RMT describes, can be used to identify deviations from the expected non-random elements or, in other words, useful signal against random noise.

In order to give a very brief explanation, according to Malik (2019), "the eigenvector is an array with *n* entries where *n* is the number of rows (or columns) of a square matrix. The below equation states that we need to find eigenvalue (λ) and eigenvector (x) such that when we multiply a scalar λ (eigenvalue) to the vector x (eigenvector) then it should equal to the linear transformation of the matrix A once it is scaled by vector x (eigenvector)."

$$A * x = \lambda * x$$

It's usual to represent eigenvalues as lambda (λ).

Marchenko-Pastur Law

Elaborating on the distribution of random matrices eigenvalues, Plerou et al. (1999) found that the distributions of most of the eigenvalues of the empirical correlation matrices correspond to what was expected by the random matrix theory. They could be associated with simple randomness, but they saw deviations for a few of the largest eigenvalues.

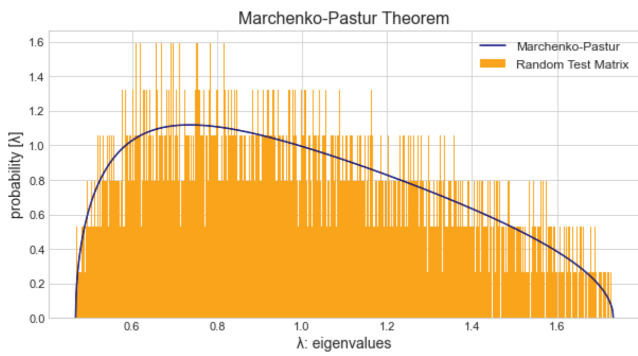
In this sense, to determine what part of the distribution would correspond to signal information and what part to pure noise, the use of the Marchenko-Pastur law (1967) has been proposed. The Marchenko-Pastur theorem states that if the elements of a matrix are random, its eigenvalues will be distributed in a given range and density. In this way, the eigenvalues that deviate from the expected theoretical Marchenko-Pastur distribution would contain useful information, such as the number of non-random factors (just by counting those eigenvalues). Not only that but the eigenvalues could be used to clean up or filter the correlation matrices, thus keeping the meaningful signal and reducing the random useless and confusing noise.

To check this let's see how it behaves in practice. Let's create a random matrix R containing 10,000 rows and 1,000 columns and compare:

- The blue line: shows the density that the eigenvalue distribution adopts when the elements of the matrix are random according to the Marchenko-Pastur law.
- The orange distribution: eigenvalues of the random matrix R are graphed thanks to the implementation of python's scikit-learn kernel density estimation (KDE).[1]

In Figure 1 the eigenvalues of this random matrix are shown in orange and it can be seen that they accurately adjust to the theoretical distribution, which means random elements.

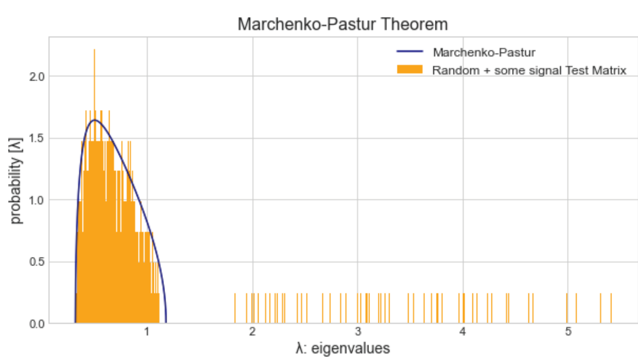
Figure 1. Fit of eigenvalues of a random matrix (orange) to its theoretical density (blue)



If this were the distribution of the eigenvalues of the portfolio's correlation matrix, it would provide no signal at all but pure random behavior (noise). However, what happens when there is signal and noise? That is, what happens when part of the behavior of the correlation matrix is random and another part is not?

Let's generate a new random matrix (8000 * 800), as we have done before, and add some signal—as is explained by López de Prado (2020)—to the correlation matrix, for example, with 100 signal factors. Following the same steps, in Figure 2 we get:

Figure 2. Random matrix (8000 * 800) with some added signal

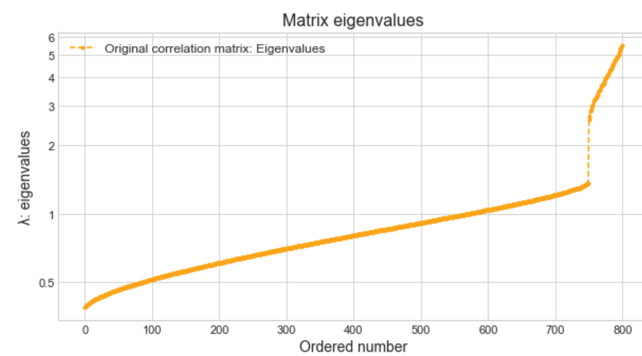


Note: We have adjusted the variance to 0.8 for a better fit (consult López de Prado [2020]).

Some eigenvalues of the matrix correspond to random behavior (blue line range) and others to non-random behavior. In other words, a part of the correlation matrix corresponds to noise and another part to signal. The question that arises almost immediately is how can we remove this random behavior? Can we modify the matrix to get rid of these eigenvalues? The answer is yes, by filtering or denoising it.

To help understand the denoising method, let's change the way in which we see the same eigenvalues of the previous figure. In Figure 3, the horizontal x-axis becomes the y-axis, and the horizontal simply show the eigenvalues from the first to the last (800).

Figure 3. Eigenvalues of previous random matrix (8000 * 800) with some added signal



Supposing the variance σ is 0.8 instead of 1 (for a deeper explanation see López de Prado [2020]), any eigenvalue above λ+ corresponds to signal:

$$\lambda \pm = \sigma \cdot \left(1 \pm \sqrt{\frac{\text{number of assets}}{\text{number of dates}}}\right)^2$$

λ+ = 0.8 * (1 + sqrt(8000/800)) ^ 2 = 0.8 * (1.316) ^2 = 1.386

So, once ordered from lowest to highest, 700 corresponds to noise (below 1.386, the λ+ level) and 100 to signal (above 1.386).

Correlation Denoising

There are several ways to clean (filter) matrices. As Bun et al. (2016) quotes:

1. Basic linear shrinkage
2. Advanced linear shrinkage
3. Eigenvalues clipping (Bouchaud and Potters, 2011)
4. Eigenvalues substitution
5. Rotationally invariant, optimal shrinkage

According to Bouchaud and Potters (2011), a way to denoise the matrix is keeping the top eigenvalues (all above the Marchenko-Pastur upper edge λ+) and shrink the others to a constant one.

Practical Case: S&P 500 Members Correlation Matrix

To carry out this research, the closing prices of the S&P 500 members have been used from approximately five years since June 1, 2016. Once insufficient data assets and dates have been removed, the logarithmic returns are calculated in a 1,349 x 474 matrix (1,349 dates and 474 assets).

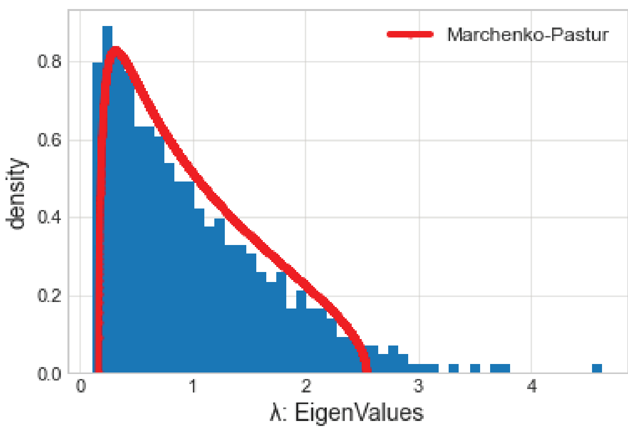
The red line shows the theoretical distribution of the random eigenvalues according to Marchenko and Pastur (1967) and the distribution of the empirical correlation matrix, as can be seen, and assuming that the variance for all of the standardized log returns is 1 ($\sigma = 1$).

$$\lambda \pm = \sigma \cdot \left(1 \pm \sqrt{\frac{\text{number of assets}}{\text{number of dates}}}\right)^2$$

The maximum theoretical eigenvalue is 2.537, so there are 18 eigenvalues higher than the maximum level:

[4.626, 3.748, 3.681, 3.457, 3.297, 3.115, 3.0476, 2.915, 2.883, 2.834, 2.818, 2.777, 2.762, 2.695, 2.674, 2.626, 2.576, 2.567] and 456 eigenvalues related to noise.

Figure 4. Empirical correlation S&P 500 members' eigenvalues distribution vs. Marchenko-Pastur



So, in order to denoise the correlation matrix, let's substitute all the 456 eigenvalues by a constant one, like the average, 0.91864.

After doing that we must reconstruct the covariance and the correlation matrices to get a filtered one.

Again, we follow López de Prado (2020). So, being:

- eVec: Correlation matrix eigenvectors
- eVal: New eigenvalues (keeping the top ones and shrinking the others to a constant one average)
- eVec' = eVec.T = Trasposed eVec matrix

$$\text{cov} = \text{eVec} \cdot \text{eVal} \cdot \text{eVec}'$$

$$\text{filteredCorrelation} = \frac{\text{cov}}{\sqrt{\text{diag(cov)}} \cdot \sqrt{\text{diag(cov)}}'}$$

Or, using python code:

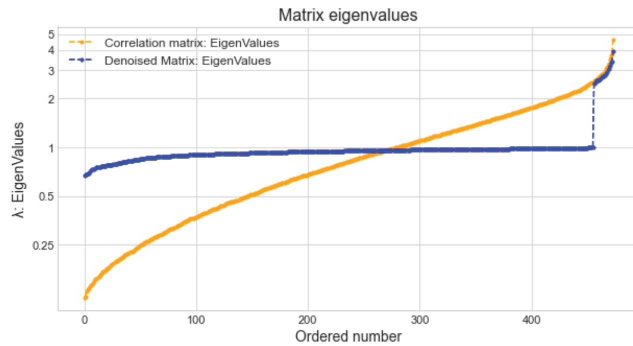
covariance = np.dot(eVec,eVal).dot(eVec.T)

That is, the covariance matrix than can be easily normalized into a correlation matrix.

Note that getting the eigenvectors and eigenvalues in Excel is possible, but there are no direct functions so some VBA code or add-in may be used. Once the eigenvalues and eigenvectors are set, just direct (but array) formulas can be used to denoise the matrix.[2]

Let's plot the results.

Figure 5. Comparison of eigenvalues before and after denoising



Although there are some criticisms about the denoising of the correlation matrices—"However, this cleaning overlooks the fact that the large empirical eigenvalues are overestimated," (Bun et al., 2016) and "However, 'no information' or 'pure noise' assumption in the bulk region is too strict…the residuals from real data are not necessarily pure noise, and more general correlation structure needs to be considered to assess the empirical densities," (Papanicolau and Yeo, 2016)—many researchers defend its use, as is the case of López de Prado (2020).

"Working with denoised and detoned covariance matrices renders substantial benefits. Those benefits result from the mathematical properties of those treated matrices and can be evaluated through Monte Carlo experiments." Furthermore, he analyzes the case of two characteristic portfolios at the efficient frontier, such as the minimum variance and maximum Sharpe ratio, concluding a very significant improvement of the root-mean-square errors (RMSE) across all weights when the correlation matrices are denoised (López de Prado, 2020).

Conclusion

In the field of financial markets, asset correlation matrices are widely used to establish the relationship between the evolution of their prices. However, since signal-to-noise ratio in financial data sets is very low, prior filtering of the matrix is recommended. This technique, known as denoising, is performed according to the Marchenko-Pastur law.

Explanatory Note on the Use of Python

Although the fact of using Python (or another similar language) could be a handicap for the dissemination of this methodology, two things may be said:

1. Being strict, Excel could be used, but with a large number of array formulas or array code that make it somewhat uncomfortable. Additionally, the calculation of the eigenvalues and eigenvectors is more complex, but possible.
2. Although programming requires knowledge and experience, the use of a third-party code, for example in Python, is not complex. Unix and Apple come with Python by default, while Windows requires a relatively simple installation. The repository, both for the code and an explanation of the Python installation, can be accessed at www.github.com/Robexia/Denoising.

Both López de Prado (2020) and Rome (2016) offer useful snippet code, although they differ in some aspects, especially in the way in which the denoising of the correlation matrix is carried out.

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Notes

[1] In statistics, kernel density estimation (KDE) is a non-parametric method that estimates the probability density function of a random variable from some observations (called sample). It was proposed by Rome (2016) and Silverman and Jones (1951). There are numerous ways to implement it in Python, for example, using the SciPy, Statsmodels, Scikit-learn, or seaborn libraries.

[2] Array formula is a special type of formula that must be entered by pressing Ctrl+Shift+Enter in a range.

Actively Using Passive Sectors to Generate Alpha Using the VIX

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Abstract

A significant amount of academic research has documented momentum within and across broad sectors of the stock market as a means of generating alpha over a passive benchmark. However, few studies approach sector allocation from a mean reversion perspective using the Chicago Board of Exchange (CBOE) Volatility Index (VIX) as the trigger. We find that positioning into defensive sectors during periods of low volatility for the stock market, and into cyclical sectors during periods of high volatility, produces significant long-term alpha. Using this framework, we backtest a dollar-neutral strategy documenting return differentials and create a modified S&P 500 Index that overweights and underweights cyclical and defensive sectors systematically based on VIX levels. Absolute and relative returns for a sector allocation strategy that uses VIX levels significantly outperforms a passive buy and hold approach by using mean reversion to generate alpha. We postulate that the approach likely works because of behavioral biases related to loss aversion and the disposition effect creating mispricings that are repeatable and exploitable during periods of extreme market stress.

Introduction

The Efficient Market Hypothesis is at the core of all traditional arguments for buy and hold investing. Because this theory postulates that all information is known and factored immediately into price, active asset allocators and traders cannot possibly outperform or have any analytical edge.[1] A major assumption for the Efficient Market Hypothesis to hold, however, is that market participants are on average rational and do not exhibit behavioral biases that cause over or underreactions in current price. We know from numerous academic studies that this simply is not true.[2] Market participants exhibit clear patterns of irrational responses to already known data, allowing for exploitable opportunities and alpha generation through the identification of near-term activity driven by emotion.

Active traders and asset allocators inherently attempt to exploit repeatable human behavior to create a better risk-adjusted return profile for their portfolios. One well-documented anomaly traders often focus on is momentum. Underreaction to positive news is often cited as the reason for why the momentum anomaly exists. Investors may be exposed to all data points that impact valuation, but the gradual diffusion of information, and hesitation to aggressively position bullishly into a particular segment of the market creates persistence in price movement and ultimately forms trends. Conversely, overreactions to all available information tend to present themselves during periods of heightened fear and risk of loss. Prospect theory[3] argues that individuals do not act rationally and value gains and losses differently, creating a bias toward loss aversion and a stronger emotional response to declining stock prices than advancing ones. Put simply, a dollar of loss is felt more strongly than a dollar of gain.

Fear of loss, rather than hope for gain, is where the most aggressive mispricing occurs when it comes to investing and is most felt during periods of heightened volatility for the stock market. Perceived risk during corrections and crashes often results in panic selling, usually at the wrong time, as loss aversion dictates actions more than any Efficient Market Hypothesis ever could. While it may be cliché to say that most investors tend to "sell bottoms," the reality is that there is ample evidence proving that market participants often act defensively after a decline in asset values has already taken place, selling winners and holding on to losers.[4]

Buy and hold index investors will argue that this is exactly why buy and hold works. If you don't care about near-term volatility, you don't risk selling at the wrong time, and as such, are better off in the long run. As investing legend Peter Lynch once said, "far more money has been lost by investors preparing for corrections, or trying to anticipate corrections, than has been lost in corrections themselves." However, this is only correct if the execution for preparing for a correction is wrong. It is the "preparation for a correction" that must be defined properly. If Black Swans[5] are considered unpredictable and are the catalyst for severe losses in markets, then the objective for active managers shouldn't be to try to anticipate exactly when a correction or crash is set to take place. Rather, it would make more sense to position oneself defensively in case there is a volatility spike and collapse in markets while still maintaining beta exposure, and then increase that beta exposure at lower prices when overreactions create discounted buying opportunities.

Sector Momentum and Crashes

One of the most studied and well-known anomalies that counters the Efficient Market Hypothesis is the existence of momentum and autocorrelation in asset prices. Moskowitz and Grinblatt in 1999 documented the persistence of returns at the one-month interval[6] across stocks and notably on the sector and industry level, while other studies show that other asset classes also exhibit such patterns.[7] As sectors and industries advance, they tend to continue to advance because they already have, allowing active traders to take advantage of trends and price drift.

While momentum continues to be an observable and exploitable phenomenon, it certainly is not guaranteed nor risk-free. Momentum as a factor for generating alpha is prone to periodic "momentum crashes," which can create "infrequent and persistent strings of negative returns. These momentum crashes are partially forecastable. They occur in panic states, following market declines when market volatility is high, and are contemporaneous with market rebounds. The low ex-ante expected returns in panic states are consistent with a conditional high premium attached to the option like payoffs of past losers."[8] Momentum studies when evaluating sector allocation strategies tend to not put the anomaly in the context of volatility and environments of heightening uncertainty for the stock market. The objective is not to buy low and sell high, but instead buy high and sell higher. Continuously chasing the best-performing sectors works until the inevitable volatility spike and crash takes place.

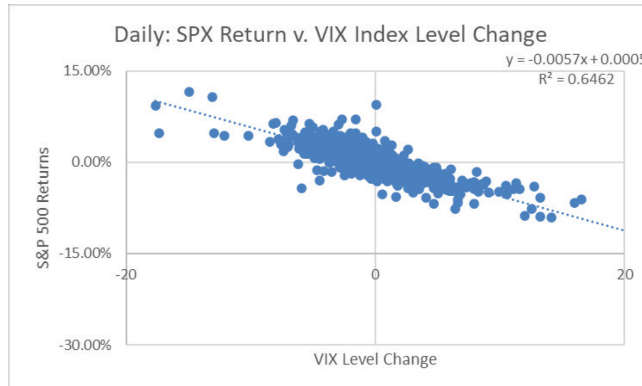
A different approach to sector positioning is to not consider momentum at all when over or underweighting against a benchmark's passive positioning. Sectors and industries may explain why momentum exists, but behavior explains why sectors get mispriced after volatility spikes. These volatility spikes may be unpredictable, but the mispricing that occurs in cyclical sectors following severe panic states for the stock market is the exact opportunity active traders should be focused on. Positioning defensively in advance of high volatility periods through lower beta sectors like Utilities, Consumer Staples, and Healthcare allows for protection prior to when unpredictable losses occur. As losses and volatility increase to unsustainable levels, the positioning out of defensive sectors into cyclical ones presents an opportunity to buy into panic and benefit from a return to normalcy, until the pattern repeats and defensive positioning during excessively low periods of volatility is warranted again.

Deconstructing the VIX

The CBOE Volatility Index, better known as the VIX, is an index designed to measure the market's expectations for volatility over the following 30 days. It does this using the CBOE's S&P 500 index derivatives contracts. Originally envisioned as a means of simply measuring volatility expectations using the S&P 100 index, the VIX has become the premier benchmark for U.S. stock market volatility. It is cited by numerous financial media outlets as the "fear index" and has spawned a number of tradable products using it as the underlying index, including exchange-traded funds (ETFs), exchange-traded notes (ETNs), and options contracts.[9]

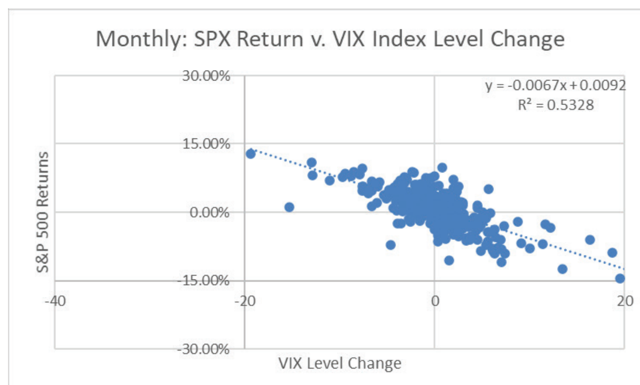
Many traders and investment managers use the VIX as part of their decision-making processes. Historically, there has been a strong negative correlation between stock market performance and the VIX (see Chart 1). This is demonstrated by looking at daily returns in the S&P 500 index in relation to daily changes in the VIX.[10]

Chart 1. Daily VIX and stock market correlation



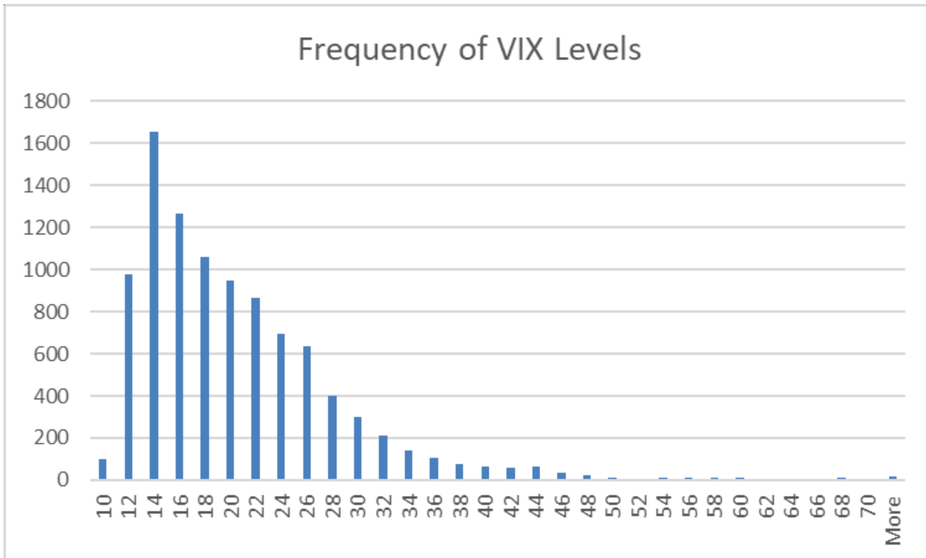
From 1990 through 2018, significant daily losses in the S&P 500 have been strongly linked to short-term spikes in the VIX. The same correlation also exists when viewing S&P 500 returns and VIX changes on a monthly basis (see Chart 2).

Chart 2. Monthly VIX and stock market correlation



Which of the two factors is more causal in this relationship is unclear, but loss aversion could be explanatory. Investors have a tendency to want to avoid losses more than generate gains. In practice, investors seeing sharp declines in financial markets often rush to sell before any further losses occur. The disposition effect[11] argues that investors sell their winners before their losers, and often times the winners before a VIX spike and decline in stocks are high beta/cyclical areas of the stock market. The overreaction takes place and brings with it an anomaly to exploit, but not often. Volatility spikes and corrective environments for stocks, while painful, are relatively infrequent. VIX levels more often than not stay in a range of 12 to 24 and experience extremes at tails that are few and far between (see Chart 3).

Chart 3. Range of VIX levels historically



Sector Returns and VIX Levels

Since high levels of market volatility, using the VIX as the benchmark, are closely tied to negative equity returns, we theorize that spikes in volatility could produce "buy low" opportunities in certain segments of the market. In Benjamin Graham's book *The Intelligent Investor,* the author discusses how investors should expect volatility when investing in equities and to use volatility to their advantage. He uses the example of "Mr. Market," a hypothetical investor who is overly emotional and reactive to prevailing sentiment instead of relying on the underlying fundamentals of any given security. Graham argues that during periods such as these, securities can become either overbought or oversold, thus creating an opportunity for outperformance.[12]

We test this theory by examining the forward-looking returns of specific sectors of the market during various periods of market volatility, as measured by the VIX. In Tables 1 and 2, we use a rolling 14-trading day average for the VIX to smooth out some of the daily fluctuations and examine sector-level forward returns both 200 trading days and 500 trading days out into the future.[13]

Table 1. Sector performance following VIX levels 200 days forward

Sector 200-Trading Day Forward Returns by Rolling 14-Day VIX
(1998 - Current)

VIX Range	Industrials	Consumer Staples	Financials	Consumer Discretionary	Materials	Energy	Healthcare	Technology	Utilities	S&P 500 Total Return
10-12	10.56%	5.21%	7.35%	9.36%	11.17%	11.28%	8.57%	14.04%	8.25%	**9.90%**
12-14	7.66%	7.28%	4.94%	7.96%	7.28%	1.46%	8.89%	11.88%	9.25%	**8.03%**
14-16	9.81%	8.73%	9.02%	9.01%	9.01%	6.92%	10.45%	12.09%	13.11%	**9.82%**
16-18	7.95%	8.17%	4.45%	9.76%	7.33%	8.15%	8.80%	7.68%	11.61%	**7.67%**
18-20	1.50%	4.62%	-0.99%	4.64%	2.90%	2.12%	3.61%	-0.40%	4.50%	**2.08%**
20-25	-1.48%	3.10%	-3.26%	1.02%	-0.12%	0.54%	0.03%	-10.12%	-0.41%	**-0.33%**
25-30	3.27%	4.52%	-0.53%	8.42%	4.91%	1.31%	1.06%	-5.22%	1.56%	**2.88%**
30-35	16.18%	8.33%	15.91%	20.83%	17.96%	9.66%	14.38%	15.72%	8.91%	**14.94%**
35-40	13.04%	6.55%	15.68%	17.82%	12.86%	8.99%	14.71%	21.09%	11.81%	**18.36%**
40-45	36.60%	22.09%	52.14%	42.80%	43.40%	26.54%	22.69%	40.52%	13.72%	**32.03%**
45-50	47.76%	25.60%	69.23%	55.90%	56.47%	30.72%	24.67%	50.48%	19.10%	**40.14%**

source: YCharts
note: the Sector Select SPDR ETFs are used to represent sectors

We find that cyclical sectors, such as Technology, Industrials, Materials, and Consumer Discretionary, tend to outperform when investing during periods of high volatility, while defensive sectors, such as Utilities, Consumer Staples, and Healthcare tend to underperform. Conversely, there is a much less discernible trend when examining the starting points of low volatility.

In Table 2, we find similar results when examining 500-day forward returns.

Table 2. Sector performance following VIX levels 500 days forward

Sector 500-Trading Day Forward Returns by Rolling 14-Day VIX
(1998 - Current)

VIX Range	Industrials	Consumer Staples	Financials	Consumer Discretionary	Materials	Energy	Healthcare	Technology	Utilities	S&P 500 Total Return
10-12	7.21%	12.54%	-7.02%	6.40%	8.66%	7.75%	9.58%	15.99%	18.19%	**8.31%**
12-14	15.93%	17.79%	10.16%	19.14%	16.12%	3.62%	20.06%	28.70%	22.19%	**18.22%**
14-16	21.26%	17.55%	18.16%	19.99%	19.34%	17.40%	22.19%	27.62%	25.24%	**20.72%**
16-18	24.60%	22.40%	20.95%	26.35%	20.53%	28.84%	28.74%	24.24%	28.66%	**23.66%**
18-20	16.84%	15.27%	13.98%	22.71%	15.62%	23.29%	18.75%	12.97%	18.94%	**15.95%**
20-25	8.45%	10.41%	4.86%	18.76%	11.86%	7.48%	12.45%	0.65%	5.49%	**6.48%**
25-30	9.80%	9.23%	0.75%	22.27%	16.29%	12.11%	11.78%	-1.18%	5.44%	**6.03%**
30-35	40.67%	23.19%	34.67%	46.99%	39.47%	40.71%	31.53%	28.37%	29.36%	**33.21%**
35-40	46.94%	23.40%	43.50%	50.07%	41.75%	46.78%	33.85%	40.40%	29.70%	**39.82%**
40-45	84.46%	40.66%	73.01%	93.05%	80.49%	66.03%	32.77%	69.29%	26.50%	**57.83%**
45-50	98.30%	43.93%	94.73%	108.90%	93.24%	71.41%	34.91%	80.25%	31.08%	**69.19%**

source: YCharts

note: the Sector Select SPDR ETFs are used to represent sectors

Again, the traditionally cyclical sectors deliver above-average performance during high volatility starting points while defensive sectors underperform. Forward-looking returns in low- to moderate-volatility periods yield only modest differences across sectors.

Given the more notable performance differences in high-volatility periods, we theorize that by overweighting cyclical sectors and underweighting defensive sectors in these high-volatility periods, we can achieve significant alpha in comparison to the S&P 500 index by waiting for such periods to take place and acting afterwards.

Sector Returns During Market Corrections

There is a generally held belief among investors that defensive and safe-haven assets, such as Treasury Bonds, Utilities, and Gold, tend to outperform during times of market turmoil. We find that regardless of whether the economy is in recession, if there is a significant correction in equity prices and levels of volatility are elevated, this flight to quality into traditionally defensive sectors and out of cyclical areas does indeed occur. However, different sectors can experience greater impacts depending on the nature of the market environment at the time.

In Table 3, we detail broad market and sector returns during five periods of significant equity market declines.[14]

Table 3. Sector returns in major market declines

	Recessionary Periods		Non-Recessionary Periods		
Start Date	3/24/2000	10/12/2007	4/29/2011	7/20/2015	9/20/2018
End Date	10/4/2002	3/6/2009	10/7/2011	2/11/2016	12/24/2018
Avg. Daily VIX	25.2	32.8	26.1	19.5	19.7
Total Returns					
S&P 500	**-45.8%**	**-54.7%**	**-14.4%**	**-13.0%**	**-19.4%**
Utilities	-26.4%	-41.4%	2.8%	8.1%	-1.6%
Consumer Staples	0.6%	-28.0%	-3.2%	-0.2%	-10.5%
Healthcare	-18.2%	-37.1%	-8.5%	-17.1%	-13.9%
Financials	-19.3%	-81.7%	-27.2%	-21.8%	-22.2%
Materials	-15.5%	-56.0%	-23.0%	-16.8%	-21.5%
Energy	-20.3%	-48.9%	-23.8%	-23.4%	-27.2%
Industrials	-32.5%	-61.4%	-20.8%	-10.3%	-23.6%
Consumer Discretionary	-19.5%	-55.8%	-9.7%	-12.8%	-21.4%
Technology	-81.4%	-49.9%	-8.4%	-10.5%	-22.7%
Total Returns (relative to the S&P 500)					
S&P 500	--	--	--	--	--
Utilities	19.4%	13.4%	17.2%	21.0%	17.8%
Consumer Staples	46.4%	26.7%	11.2%	12.7%	8.9%
Healthcare	27.6%	17.7%	5.9%	-4.1%	5.5%
Financials	26.5%	-27.0%	-12.8%	-8.8%	-2.8%
Materials	30.3%	-1.3%	-8.6%	-3.9%	-2.1%
Energy	25.4%	5.8%	-9.3%	-10.4%	-7.8%
Industrials	13.3%	-6.7%	-6.4%	2.6%	-4.3%
Consumer Discretionary	26.3%	-1.1%	4.7%	0.2%	-2.0%
Technology	-35.6%	4.8%	6.0%	2.5%	-3.4%

The two recessionary periods were marked by severe underperformance in the sectors largely attributed to causing the recession. During the dot-com bubble, Technology was a massive underperformer. During the financial crisis, it was Financials that were the biggest losers. Outside of those two sectors in those recessions, we can conclude that defensive sectors, such as Utilities and Consumer Staples, outperformed the S&P 500, but the remaining sectors were inconsistent in their returns.

In the three non-recessionary periods measured, however, there are more distinct patterns of defensive and cyclical sector performance. We note that Utilities and Consumer Staples were strong outperformers and beat the S&P 500 by at least 9% in all measured periods. The more traditional economically cyclical sectors, such as Financials, Materials, Energy, and Industrials, underperformed in 11 of the 12 instances. The consumer-cyclical sectors, including Consumer Discretionary and Technology, produced mixed results but demonstrated the ability to beat the S&P 500 despite heightened market volatility. From these results, we can establish that investors do tend to rotate into more conservative market sectors during periods of above-average market volatility that often

From these results, we can establish that investors do tend to rotate into more conservative market sectors during periods of above-average market volatility that often correlate with meaningful declines in the value of equities. The clear beneficiaries of this defensive rotation are the Utilities and Consumer Staples sectors.

The Trigger

The above shows that when the VIX is at a particular level, certain sectors outperform in the subsequent 12 months. With this in mind, an optimal trigger level needs to be defined for when cyclical sectors are expected to outperform defensive sectors in the subsequent periods. An additional trigger is required for when one should switch positions from cyclical sectors to defensive sectors. To do this, Nelder-Mead optimization is performed over a learning period.

There are two methods used to determine the learning periods applied. The first is a static period between January 1, 1999, and December 31, 2004. The second is a rolling five-year period with the first period between January 1, 1999, and December 31, 2004. Subsequently, the oldest month is dropped and a new month is added, with the final rolling period being September 1, 2014, to August 31, 2019. This means that the trigger level will vary through time.

In addition to this, one could equally weight their investment in cyclical and defensive sectors to create a cyclical and defensive index, or one could use the sector weightings of a passive benchmark such as the S&P 500 to reconstruct an index. Both possibilities were used in generating the optimal trigger.

In Table 4 and Charts 4 and 5, the results of the static and the rolling trigger levels for equally and sector-weighted indices are shown.

Table 4. VIX trigger levels

Entry & Exit Levels - Static Training Period		
	Equally-Weighted	Sector-Weighted
Entry VIX Level	33	36
Exit VIX Level	12	12

For both equally-weighted and sector-weighted indices, the difference between the initial entry trigger and exit trigger is very high. This gap closes through time, although it has widened again since 2018. This could be an indication that a more volatile market climate may lead to a greater differential in the trigger levels.

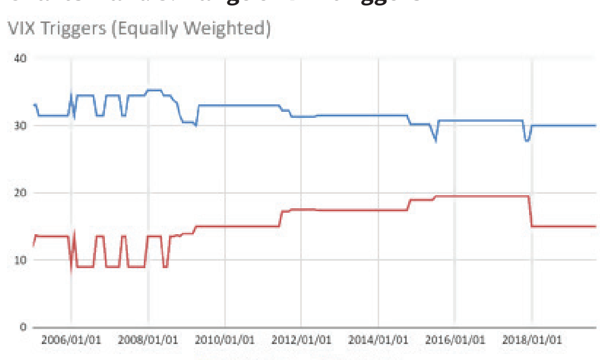
Trading Strategies

To determine whether one could use the VIX as a sector allocation tool, three different trading strategies are created. The first, dollar-neutral, is where, when the entry trigger level is reached, one goes 100% long the cyclical index and 100% short the defensive index, with this reversed when the exit trigger level is reached. The second, sector-rotation, is where, when the entry trigger level is reached, one rotates fully into the cyclical index and out of the defensive index, with this reversed when the exit trigger level is reached. Finally, the sector overweight and underweight strategy increases the cyclical index weight by 5% of its respective S&P level when the entry trigger level is met, reducing the defensive index weight by 5%, and inverting this when the exit level is met. These trading strategies are implemented using both equally and sector-weighted cyclical and defensive indices and using a static and rolling training period for optimization. To mirror the actual returns that one would generate, the SPDR sector ETFs are used.

Dollar-Neutral Strategy

The dollar-neutral strategy is one where the pure alpha of differential returns based on a VIX trigger level can be discerned. Because it is dollar-neutral, the returns would be expected to be lower, but this should also be met with lower risk, meaning higher risk-adjusted returns are possible. The different performance metrics for the four variants of the strategy are calculated in Table 5.

Charts 4 and 5. Range of VIX triggers



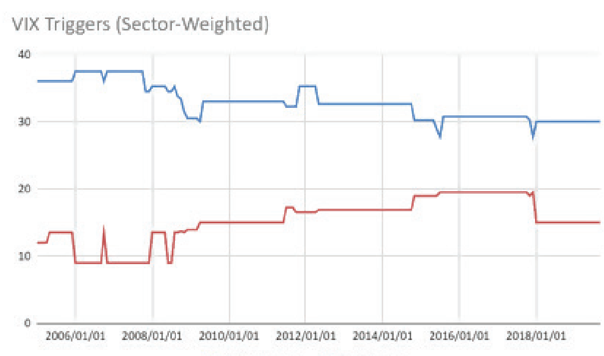


Table 5. Dollar neutral returns

	Equally-Weighted (Static Training)	Sector-Weighted (Static Training)	Equally-Weighted (Rolling Training)	Sector-Weighted (Rolling Training)	S&P 500
Return (Annualized)	3.34%	3.89%	5.82%	5.54%	8.92%
Risk (Annualized)	11.25%	10.40%	11.23%	10.39%	16.47%
Risk-Adjusted Return	0.30	0.37	0.52	0.53	0.54
Maximum Drawdown	-33.94%	-31.98%	-31.84%	-30.81%	- 55.25%
Upside Capture (%)	9.71%	10.29%	-7.43%	-2.49%	
Downside Capture (%)	7.21%	7.29%	-14.11%	-8.40%	

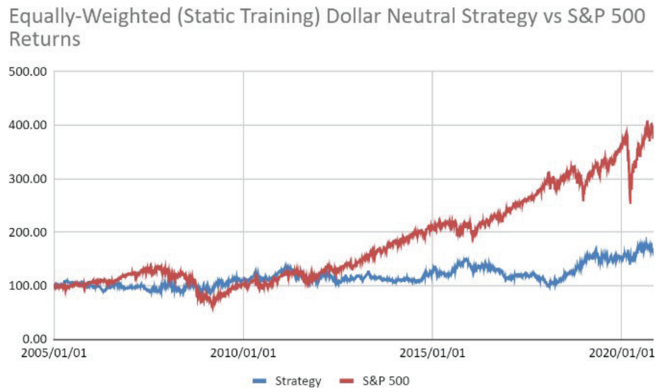
There are two clear findings that can be drawn from the above. The first is that the dollar-neutral strategy has lower risk compared to the S&P 500. The second is that the choice of learning method to generate the VIX trigger levels leads to significantly different return.

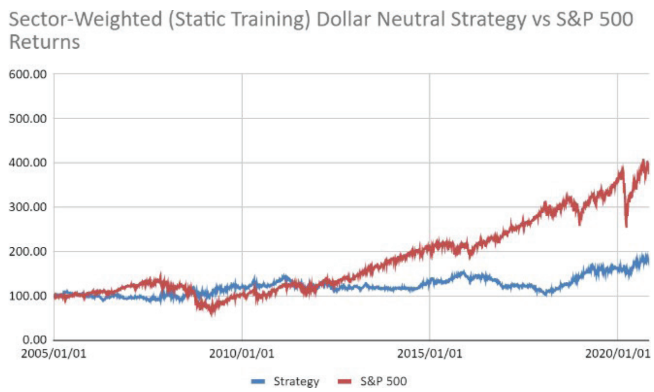
Across all variants, the portfolio is long the defensive index and short the cyclical index until mid-2008, when there is a switch across to cyclical stocks. There is also a move towards

Across all variants, the portfolio is long the defensive index and short the cyclical index until mid-2008, when there is a switch across to cyclical stocks.There is also a move toward the defensive index in 2012 lasting to 2016 across all variants. However, there are clear differences between the different training methods used and the sector plays. In the equally-weighted trading strategy using a static training period, there are fewer switches across indices compared to the rolling training period. This lack of switching is most likely the reason for the relative underperformance, as the cyclical or defensive indices are held on for too long a period. The opposite occurs with the sector-weighted indices, with a static training period leading to many more switches. In this case, this would lead to underperformance, as the defensive or cyclical index is traded out before the returns have been fully realized. This also explains the upside capture being negative and downside capture being more negative, as the strategy is more often exposed to shorting high beta cyclical sectors that perform strongly in bull markets until the VIX spike occurs.

Finally, the performances through time are decomposed to determine the times where the strategy performs and the times it does not. These performances are graphed in Charts 6 and 7.[15]

Charts 6 and 7. Dollar-neutral versus S&P 500 (static)

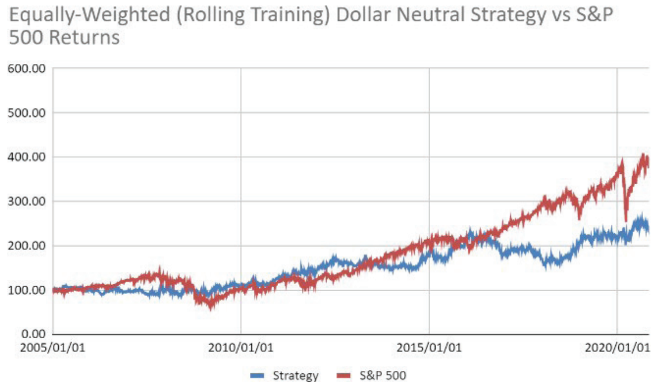


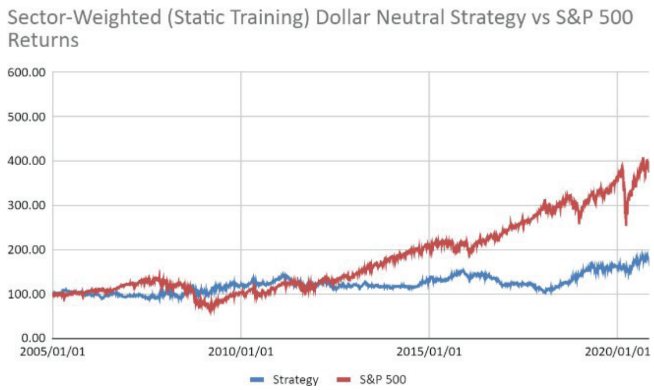


Using a static training period to optimize the VIX levels leads to fairly flat performance through time, irrespective of the weighting methodology used. There is clear alpha generated in 2008, as the strategies are long defensive stocks and short cyclical stocks, and again in 2016. However, that alpha is slowly eroded through time. One anomaly is that the equally weighted portfolio, using this training method, is long cyclical stocks and short defensive stocks from 2019—the only variant of the strategy that is. As such, it is receiving some negative alpha due to market conditions during that evaluation period.

Unlike the returns created using the static-training-period-generated VIX trigger levels, the returns created using the rolling-training-period-generated VIX trigger levels show a clear upward trend (see Charts 8 and 9). Both variants remain flat through the subprime crisis and then generate alpha as cyclical stocks rebound. The performance then flattens from 2012 to 2015 as a defensive play is held; however, this then yields positive performance during the volatility of the 2015 market. This erodes during the subsequent market run but is made up during the changed market conditions where defensive stocks are outperforming.

Charts 8 and 9. Dollar-neutral versus S&P 500 (rolling)





All-In Sector Rotation Strategy

The sector rotation strategy allocates 100% to either the cyclical index or the defensive index. Unlike the dollar-neutral strategy, the performance of the strategy is also dependent on the movement of the market, as it always has beta exposure (see Table 6). The performances of the four variants of the strategy are tabulated below.

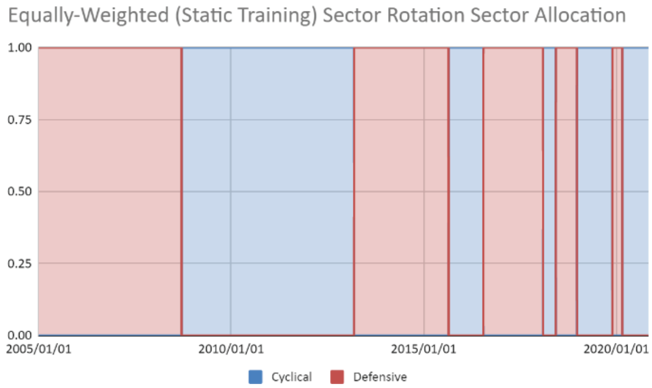
Table 6. All-in rotation strategy returns

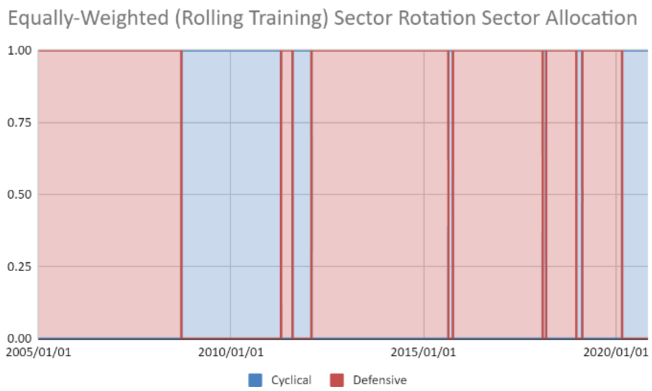
	Equally-Weighted (Static Training)	Sector-Weighted (Static Training)	Equally-Weighted (Rolling Training)	Sector-Weighted (Rolling Training)	S&P 500
Return (Annualized)	10.63%	11.06%	12.04%	12.00%	8.92%
Risk (Annualized)	17.60%	17.65%	16.96%	17.12%	16.47%
Risk-Adjusted Return	0.60	0.63	0.71	0.70	0.54
Maximum Drawdown	-54.54%	-52.51%	-54.54%	-52.51%	-55.25%
Upside Capture (%)	96.07%	97.77%	88.24%	91.53%	
Downside Capture (%)	94.14%	95.54%	84.34%	87.91%	

The absolute and risk-adjusted returns for all four variants exceeds that of buying and holding the S&P 500. The annualized risks are greater than the buy-and-hold strategy, but the maximum drawdowns are roughly the same. Across the variants, using a rolling training period to optimize the VIX trigger levels yields greater absolute and risk-adjusted returns. While no strategy is able to "keep up" with the S&P 500 fully, given upside capture ratios that are less than 100%, this is countered by downside captures being less than upside capture. Alpha, it appears, comes not from being up more with the strategy, but rather by being down less prior to the volatility spike and decline in equities.

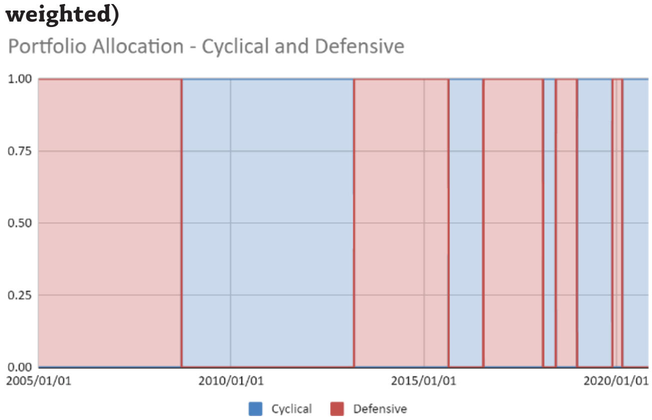
Charts 10 through 13 show the rotation across cyclical and defensive indices through time. As the triggers are the same as the dollar-neutral strategy, the rotations occur at the same time. However, because it is a full sector rotation, these weights remain 100% until the next switch.

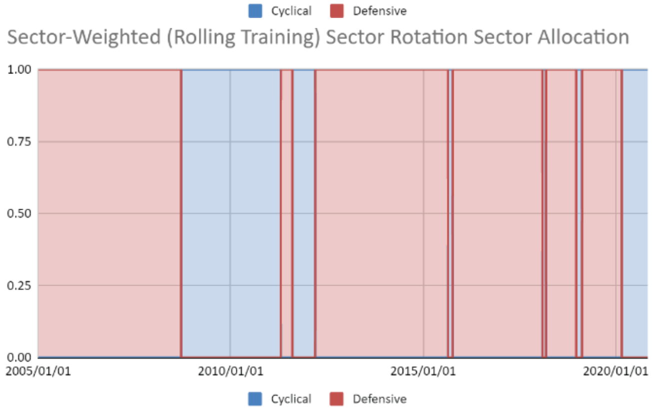
Charts 10 and 11. Sector rotation allocation (equally-weighted)





Charts 12 and 13. Sector rotation allocation (sector-weighted)

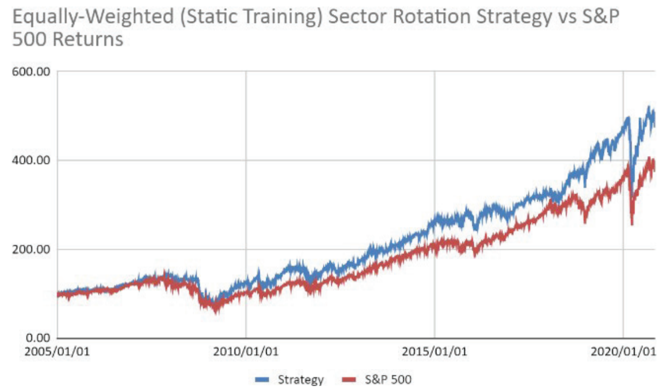


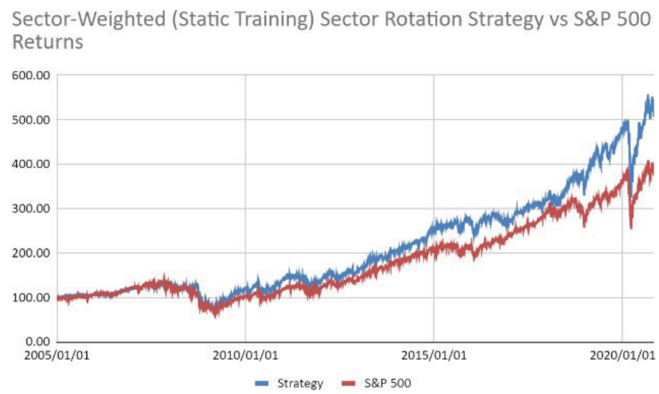


The same underlying themes are seen here. There is movement from defensive to cyclical sectors during the subprime crisis. In most of the subsequent periods, defensive stocks are held barring a few short periods where they are rotated into cyclical stocks.

Finally, the performances through time are decomposed to determine the times where the strategy performs and the times it does not. These performances are graphed in Charts 14 through 17.

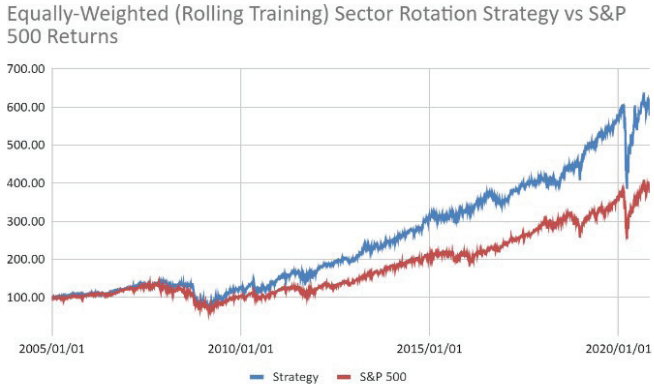
Charts 14 and 15: All-in sector rotation strategy versus S&P 500 (static)

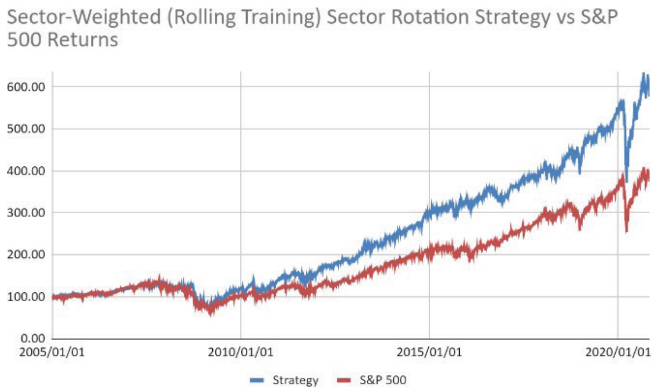




Using the static-training-period-generated VIX trigger levels, the equally-weighted and sector-weighted strategies outperform the S&P 500 buy-and-hold strategy across most time periods (see Charts 14 and 15). As defensive stocks are held until mid-2008, the strategies outperform the buy-and-hold strategy before they switch into cyclical stocks and have similar negative returns. However, in the period after, they recover quicker, leading to outperformance compared to the buy-and-hold strategy. This outperformance continues across time, with there being particularly strong performances in 2019.

Charts 16 and 17: All-In Sector Rotation Strategy Versus S&P 500 (Rolling)





Much like the strategies derived from the static training period generated VIX trigger levels, the strategies derived from the rolling training period generated VIX trigger levels also outperform a buy-and-hold strategy in most market conditions (see Charts 16 and 17).

However, the magnitude of outperformance in these variants is greater than in the preceding variants.

Active Overweighting/Underweighting Sectors

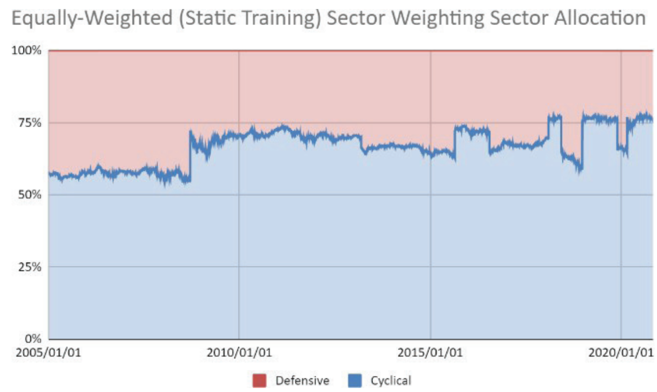
While the sector rotation strategy is a possible trading strategy, it is more likely that one would overweight or underweight cyclical or defensive sectors based on the VIX trigger level rather than do an all-in approach. In this trading strategy (see Table 7), when the VIX entry trigger level is reached, cyclical sectors are overweighted by 5% and defensive stocks are underweighted by 5%, with the inverse occurring when the VIX exit trigger level is reached.

As per the sector rotation strategies, the sector overweight/underweight strategies outperform an S&P 500 buy-and-hold strategy in both absolute and risk-adjusted returns. The annualized risk is also lower, as is the maximum drawdown. Using a rolling training period to generate the VIX trigger levels compared to using a static training period to generate the VIX trigger levels leads to marginally higher absolute and risk-adjusted returns.

The allocations to the different sectors are derived from the same triggers used earlier.

However, as they are cognizant of the market weightings as a whole, at most 50% of the strategy is allocated to defensive stocks, and at most 75% is allocated to cyclical stocks (see Charts 18 through 21). This brings them closer in line to the market as a whole through time.

Charts 18 and 19. Defensive/cyclical weighting through time (equally-weighted)



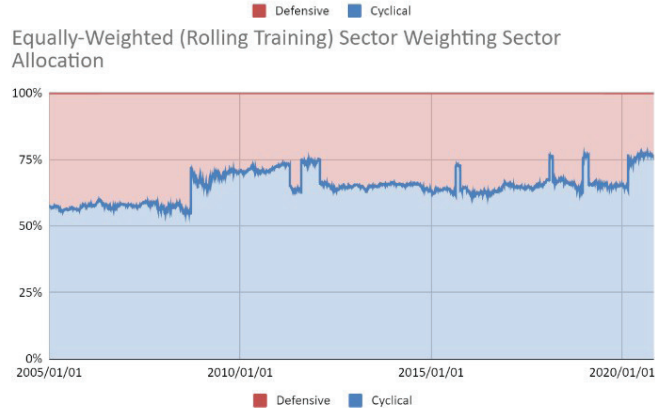
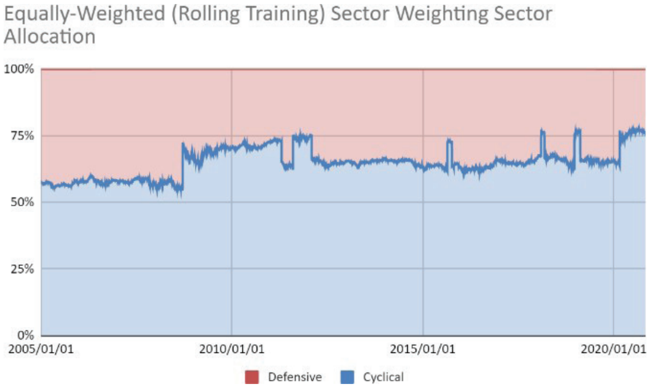
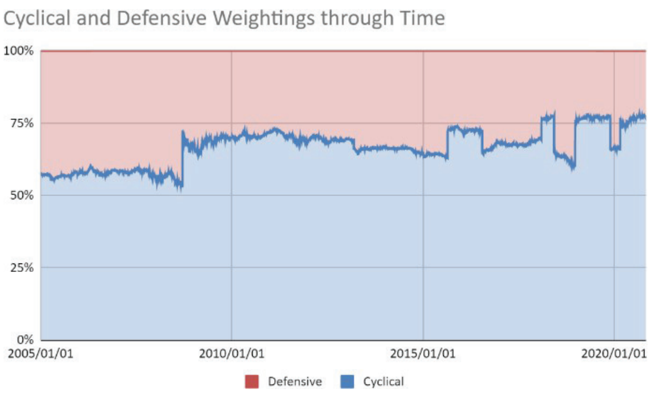


Table 7. Active overweighting/underweighting strategy returns

	Equally-Weighted (Static Training)	Sector-Weighted (Static Training)	Equally-Weighted (Rolling Training)	Sector-Weighted (Rolling Training)	S&P 500
Return (Annualized)	9.34%	9.80%	9.40%	9.81%	8.92%
Risk (Annualized)	16.07%	16.14%	16.02%	16.11%	16.47%
Risk-Adjusted Return	0.58	0.61	0.59	0.61	0.54
Maximum Drawdown	-51.41%	-51.82%	-51.41%	-51.82%	-55.25%
Upside Capture (%)	96.87%	97.92%	96.30%	97.49%	
Downside Capture (%)	96.22%	96.91%	95.54	96.44%	

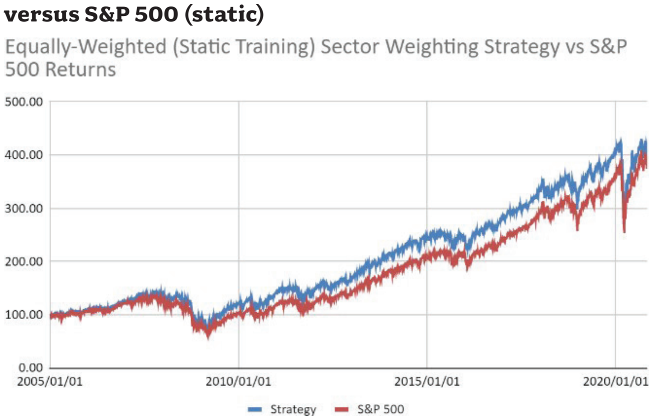
Charts 20 and 21. Defensive/cyclical weighting through time (sector-weighted)

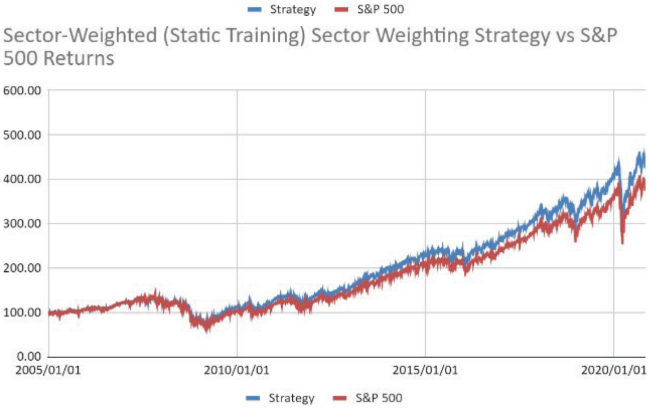




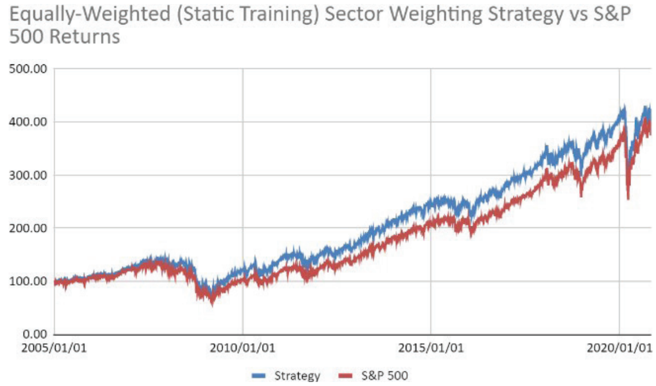
Finally, the performances through time are decomposed to determine the times where the strategy performs and the times it does not (see Charts 22 through 25). These performances are graphed below.

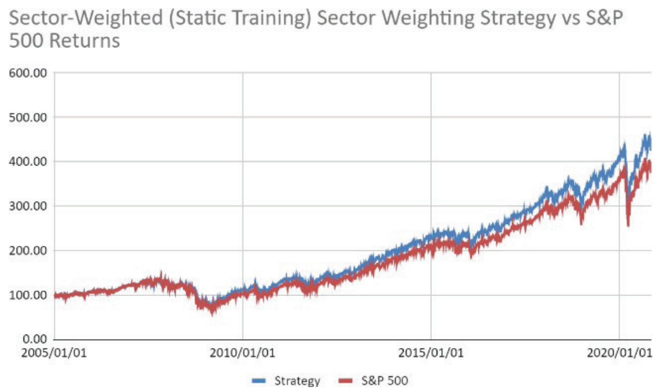
Charts 22 and 23. Active overweighting/underweighting versus S&P 500 (static)





Charts 24 and 25. Active overweighting/underweighting versus S&P 500 (rolling)





Due to the sector allocations being more in line with the S&P weightings, the magnitude of over or underperformance is much lower than in the previous strategy. However, it is clear that, across all four variants, this trading strategy outperforms a buy-and-hold strategy in almost all market conditions, with relative sector weighting being between a minimal band of plus or minus 500 basis points.

Why It Works

Is this simply a function of mean reversion, whereby cyclical sectors following VIX spikes suffer steeper losses than are justified, in turn creating an exploitable opportunity relative to defensive stocks after the spike has occurred? Perhaps. Volatility is inherently mean-reverting. A VIX spike can't persist forever and stay elevated for a particularly long period of time, as that would imply a near-permanent bear market and decline in equities to zero.

A more behavioral explanation, however, relates to how cyclical sectors, which tend to have higher sensitivity to bull market factors, behave prior to a corrective environment for stocks. If cyclical areas of the market tend to go up more and are the "winners" of investor portfolios, then the disposition effect means that when volatility accelerates, those winners are the first to be sold, as the relative underperformers up to that point are held. The overreaction to losses and preferred method of selling winners first creates a mispricing and misallocation effect that can be potentially arbitraged for active investors and traders afterwards.

The challenge of course with such an approach to sector allocation is being defensive waiting for those levels to present a buy low opportunity in cyclicals. This can be quite challenging from an implementation standpoint, as it implies not being aggressively positioned in areas that could go up at a faster pace than the averages if the positioning is defensive throughout, preparing for the unknown timing of a correction that could take time to present itself.

The fact that all variations of the strategy have an up capture that is less than 100% because of defensive positioning would likely test the patience of investors implementing such an approach. Fear of missing out on a strong bull market can be a strong reason to not be defensive throughout. Yet, that is exactly why the strategy outperforms.

This intuitively makes sense. Being defensive in advance of a correction means the portfolio is up less during an extended bull run when investor complacency is taking place and performance momentum defines investor allocation decisions. When the volatility spike occurs, it is this defensiveness that saves the portfolio from the overreaction on the downside that occurs primarily in cyclicals.

Conclusion

While momentum is often touted as the ideal anomaly to take advantage of using sectors to express an active bet on continued performance, we find that an approach that waits for momentum to crash with a VIX spike allows for an ideal setup to buy low and sell high when investor overreactions take place. We test various methodologies and strategies, all of which come to the same conclusion around using extreme VIX levels as trigger points to determine how aggressive or defensive to get with sector allocations. While one can never know the exact moment an extreme period of volatility and collapse in stocks takes place, one can be confident that it is worth being defensive before it happens. After it does, going full speed ahead when all is clear becomes the preferred way of positioning a portfolio until another extreme is reached. Mean reversion using the VIX to overweight or underweight sectors ultimately outperforms the mean of a passive strategy.

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Notes

[1] *See* Malkeil (2003).

[2] *See* Philip and Torbey (2002).

[3] *See* Kahneman and Tversky (1979).

[4] *See* Barber (2011).

[5] *See* Taleb (2007).

[6] *See* Moskowitz and Grinblatt (1999).

[7] *See* Luu and Yu (2012).

[8] *See* Daniel and Moskowitz (2015).

[9] Chicago Board Options Exchange (CBOE). "CBOE Volatility Index – VIX White Paper," CBOE, http://www.cboe.com/micro/vix/vixwhite.pdf.

[10] *See* Bhave (2018).

[11] *See* Fogel and Berry (2006).

[12] *See* Graham (2006).

[13] 200- and 500-trading day periods are meant to roughly approximate one-year and two-year forward returns.

[14] To define sectors, we use the SPDR Select Sector ETFs (https://us.spdrs.com/en/product/view-all-low-cost-core?cid=0). The nine ETFs used were all launched on 12/16/98. Prior to 10/7/15, the financial sector included both Financials and Real Estate before Real Estate was spun off into its own sector. Prior to 6/18/18, the Technology and Consumer Discretionary sectors included Communication Services companies before Communication Services was spun off into its own sector.

[15] In all backtesting that follows, we start in a defensive position at the beginning of 2005 because the exit trigger level was reached at 12/16/2004 and it didn't hit the entry level at the point we started.

The Taylor Trading Technique *by George Douglas Taylor*

Reviewed by Regina Meani, CFTe

George Douglas Taylor was a grain trader at the Chicago Board of Trade in the 1950s. Through his tireless bookkeeping, hence the name "The Book Method," Taylor found that the grain markets moved in a three-day cycle. The Book Method aims to make a profit for the daily trader based on the rise and fall of the daily movements of the markets. Taylor propounded it was not a charting method, but I tend to disagree as much of his methods can be translated into technical analysis.

In chapter I, his references to manipulation can be transferred to read supply and demand. For example, "a movement more or less mechanical in it's action for tactics of manipulation do take on a mechanical action after a while and for the simple reason of the pattern prices form through repetition"[1]

Keeping in mind that Taylor's Book Method was introduced in the 1950s, I took Linda Bradford Raschke's advice and skipped chapters II, III, and IV, and agree that manually making a book is not really required in today's technological world. His concepts, however, are useful for traders and deal with identifying objective points for buying, selling, and short selling on a daily basis. Taylor believed that his methods trained one to rely on their own judgements with the Book Method providing the trader with all the tips one would require.

In the first chapter, he describes the three-day trade cycle with the fourth and fifth days becoming the first and second days of the next cycle. Here Taylor advises using the first day for buying and the second and third days for selling. This points us to the explanation of the three-day trading method found in chapter XIII. But before heading to this chapter one needs to understand how a buying day and a selling day are selected in chapters V through VII. More than one reading of these chapters may be needed, as I must admit that on first reading, I found the concepts a little difficult to grasp.

Clarity arrives somewhat in chapter XV where we learn about pertinent points and we find that Taylor gives "pertinent" advice that is beneficial to any trader. He states, "never make a trade unless it favours your 'play,' it is better to pass up the entire trading session than to buy or sell on a guess."[2] A few pages later he gives more advice, "a trader with any method or system of trading must develop and have a certain amount of confidence in it—with this means of trading he must believe in the occurrence and recurrence of the past pattern of movement."[3]

While I have been reading through the chapters, like Linda Bradford Raschke, I have found myself visualizing candlesticks as a representation of Taylor's trading methods. The above quote referring to the occurrence and recurrence of the past pattern of movement seems to sanction this.

Further clarity arrives in the final section of the book, which is an exert from George Angell's "Winning in the Futures Market." Taylor describes his trading methods as on a buy day the prices open at or fall to a low and then rise. A sell day is identified by prices trading at, below, or slightly above the previous day's high. On a short sell day, prices push up and halt in resistance to be rebuffed. The cycle then begins again. This method sounds simplistic, but sometimes the simplest methods work.

However, the unpredictability of the market can play havoc with the simple three-day cycle. George Angell tackled this problem and developed the LSS Three-Day Cycle Method,[4] creating an element of flexibility for the system. He changed Taylor's names to avoid confusion to "Long, Sell and Short Sale," with the main point of the conversion that one can either buy or sell on any day.

George Angell calls Taylor's Book Method the genesis of a trading system, and that over the years it has become something of an underground classic for futures traders. I find that Taylor's own words sum up the benefits of reading about his system when he says "a trader must not be so rigid as to stick to a stubborn theory. Successful speculation is not based on any set of inflexible rules and a trader must be ready to change when conditions change, however, the trader who knows how to act when the expected happens, is in a better position to act when the unexpected happens."[5] Timeless advice from an experienced trader.

Notes

1 Taylor, G.D., *The Taylor Trading Technique,* Steven Star Publishing, Australia, 2016. p. 8.
2 Ibid, p. 73.
3 Ibid, p. 76.
4 Ibid, p. 109.
5 Ibid, preface.

In Remembrance: J. Welles Wilder Jr.

June 11, 1935–April 18, 2021
Christchurch, New Zealand

A Farewell to One of the Greatest Technical Analysts in History

It seems like yesterday that I was given the honor and pleasure of presenting the IFTA Lifetime Achievement Award to Welles Wilder during IFTA's 2020 Online Annual Conference.

It was long overdue, not only because the work and contribution of Welles was revolutionary on many levels, but also because his work helped countless technical analysts worldwide to improve their analysis and therefore make better investment decisions.

As technical analysts, we are all using at least one of the indicators and systems developed by Welles, such as the DMI System, the Relative Strength Index, the Average True Range, or the Parabolic SAR, to get better market insight.

But Welles was even more than that. In his personal life, he was also a great husband, father, and friend. While Welles could not receive the award himself, Tom DeMark—his close friend for over 40 years—accepted the reward on his behalf, sharing memorable stories about their decades together as colleagues and close friends.

I am grateful thinking of that touching moment when Welles' daughter, Catherine, was with us during the conference. I still hear her loving words about Welles being a dad and a husband. Truly a very special moment that all who attended will never forget.

Welles leaves a big gap—as a husband, father, friend, and colleague.

We have to say farewell now, but we never will forget Welles and the contribution he made to all of us. His legacy continues in our charts, and this is handed down from one generation of technical analysts to another. This is IFTA's duty, and we are grateful to fulfill it.

–Wieland Arlt, 2021 IFTA President

J. Welles Wilder Jr. (June 11, 1935–April 18, 2021) was an American mechanical engineer turned real estate developer. He is best known, however, for his work in technical analysis. Wilder is the father of several technical indicators that are now considered to be the core tenets of technical analysis software. These include Average True Range, the Relative Strength Index (RSI), Average Directional Index, and the Parabolic SAR.[1]

John Welles Wilder was born June 11, 1935, in Norris, Tennessee. The oldest of four children to John Welles "Jack" Wilder Sr. and Frances Green Wilder, his brother was former NFL Defensive Tackle and Defensive End Albert Green "Bert" Wilder (April 14, 1939 – December 5, 2012).

After serving in the Korean War in the U.S. Navy, Welles attended North Carolina State University in Raleigh, graduating with a degree in mechanical engineering in 1962. He married Eleanor Dawn Barefoot on July 6, 1958. They had three children: John Welles "Johnny" Wilder III (April 22, 1959–March 25, 2020), Catharine Cooper, and David Wilder, settling in Greensboro, North Carolina. After a successful real estate practice, he founded Trend Research LTD and its primary subsidiary, The Delta Society. He then published *New Concepts in Technical Trading Systems* in 1978.

Welles and his wife retired and relocated to Christchurch, New Zealand, in October 1999, becoming dual citizens shortly thereafter. While in retirement, he continued with system development until 2008. He died on April 18, 2021, in Christchurch at the age of 85.

(Source: Wikipedia)

IFTA's 2020 Lifetime Achievement Award

IFTA's 2020 Lifetime Achievement Award was presented to a man who revolutionized technical analysis. In the mid-1970s, J. Welles Wilder Jr. created a set of indicators that was considered revolutionary because the indicators proved optimal during the sideways period that the market was experiencing during those years.

His indicators, however, stood the test of time and proved to be of great value, even when the markets witnessed strong trends. The approach worked well in the 70s, 80s, 90s, and 2000s.

Welles was a real genius and understood very well the mechanics of market movements, which was obvious in his simple but concrete definitions of upward and downward movements in addition to the relative comparisons between buyers and sellers that he always used in a very professional manner.

Welles' DMI system is one of the most well-built systems in technical analysis. It is a concrete system that gives you clear information about market direction and how strong the move is, in addition to clear overbought and oversold signals. It is important to note the DMI system (in my opinion) is the only system that can give you a real overbought situation during an uptrend and a real oversold situation during a downtrend. This is one of the techniques that is very much underrated in this system.

Other great indicators include RSI, Parabolic (SAR), and Average True Range. Professionals that used Welles' indicators know well that they contain real value—much more than was actually written in his books.

Welles was 85 years old, and his achievements in technical analysis are endless. He will remain one of the greatest technical analysts in history. There is no doubt about that. Thank you, Welles, for all you have done for our industry and for technical analysis. We all love and respect you.

—IFTA Education Committee 2021

Tom DeMark accepted the IFTA Lifetime Achievement Award on behalf of Welles Wilder Jr. and his family at the IFTA 2020 Virtual Annual Meeting on Saturday, October 24, 2020.

Hello IFTA members,

It is an honor for me to be here and accept the distinguished IFTA Lifetime Achievement Award on behalf of Welles Wilder and his family. As you may already know, Welles' health prevents him from being with us at this time and, logistics are such that his wife Dawn and children, Catherine and Ron, are unable to be here as well.

My history as a market technician spans over five decades. Looking back over those years, I recall the two most influential commodity industry pioneers who certainly influenced my life, and I am certain those of you who were around in the 1970s and 1980s will agree, were Larry Williams and Welles Wilder. Larry's history and influence reverts to the 1960s and Welles to the mid 1970s.

It's pretty common knowledge that Larry Williams' industry roots and influence have affected, one way or another, each and every one of us. He has personally, unselfishly, and willingly given his time and effort to many of us in our pursuit to share our market timing tools and beliefs. I was one of his early disciples. So too was Welles.

Welles' background as an engineer and his understanding of mathematics gave him a special edge and insight into identifying price relationships within the commodity markets. He believed many of the theories he applied as an engineer also had application to price patterns and number series. He became fascinated with the commodities markets and in turn adapted and used these concepts to develop commodity trading timing models.

At the time when Welles was working on these timing tools—1975 and 1976—he introduced himself to Larry and me. We were impressed by his intellect, modesty, and passion for the markets. What even impressed us more was his sincerity, honesty, and willingness to share. His ideas were fresh and original. At the time, other than Larry Williams book *How I Made a Million Dollars Trading Commodities* and his book on seasonality, as well as his seminars, there was total absence of any timing tools available to commodity traders. Other than what Larry popularized, most traders relied upon the three basic approaches to analysis: specifically, trendlines, moving averages, and most often, guessing. Larry and Welles changed the industry for the better. Welles created indicators that enabled traders to monitor the pulse and price behavior of the commodity markets. It was an awakening to new and vibrant methodologies designed to measure the activity of the commodity markets. Not only did these indicators strike a chord with commodity traders, it also attracted new traders who previously were unwilling to effectively gamble in commodities during the inflation riddled 1970s. They now had methods they could use to time their trades.

Larry connected Welles with Al Schmidt and his son, Steve, at Windsor Books, who published Welles' book *New Concepts in Technical Trading Systems,* which showcased Welles' contributions to the industry and for which he became legendary.

Welles was always soft-spoken and possessed a pleasant, calming demeanor, the antithesis of the nature of most commodity traders. What struck me most was his patience and willingness to share with others. He was always upbeat and had contagious laugh.

It is an honor to accept such a distinguished award on behalf of an industry titan upon whose shoulders many of us have stood. His example as an industry professional and leader, as well as a friend, is an inspiration to all of us.

Thank you, IFTA, for honoring such a deserved individual as Welles Wilder. I know he and his family appreciate this recognition and will be the highlight of his storied career.

—Tom DeMark, Creator of the DeMARK Indicators® and the founder and CEO of DeMark Analytics, LLC

I knew Welles Wilder before he was famous...

Before anyone had heard of Welles Wilder, we had become pen-pals (back then, there were no computers, no email; people wrote letters to one another). Welles had developed a moving average trading system and put together a group of really bright guys to develop market tools. In one of the think tank groups was the very bright and gifted Gresham Northcott, who I already knew, so I was excited to see what Welles would come up with.

At that point, no one knew of Welles and his group. After a year of hard work, Welles asked if I would help him spread the word of a strategy they had developed. I said, "Sure, what do you want me to do?" Welles replied, "No one has ever heard of me, would you do a mailing for me, and maybe Tom DeMark could help as well." Tom and I agreed ... and the rest is history.

Welles' books broke sales records, and his indicators shattered the traditions of how people look to trade.

Most anyone can come forward with one new market indicator or approach, but few have ever been as productive as Welles, who brought forth a plethora of ideas—from the Adam Theory to the wildly popular Delta Phenomena. Welles invited me to his home to personally teach the Delta secrets to me. What an experience that was and to see another side of Welles and his wife.

He was as passionate about his car collection as he was about the markets. Indeed, Welles had the Jay Leno car collection of traders. People rave about the ideas he brought to the markets, and rightfully so. His ideas will always be remembered. What I will remember the most is the southern kindness and courtesy he showed me—before and after he became famous.

—Larry Williams

Larry Williams is the author of 11 books, most on stocks and commodity trading.

Welles Wilder's Great Work

The Directional Movement Index and the ADX

By Saleh Nasser, CMT, CFTe

Most trend-following systems that generate the best profits are successful when a trend is underway. Usually, trend following systems lead to very good results because it is during trending periods that the vast majority of profits are achieved. During sideways periods, however, these systems lead to many losses and whipsaws, leaving the investor in agony. It is understood that during sideways periods other overbought/oversold oscillators should be used, like the Stochastic or RSI.

The best systems to use during trends are trend-following systems, like moving average crossovers, breakout systems, etc. During sideways periods, oscillators are preferred.

Fortunately, we have an indicator that tells us if the market is in a trending mood or in a trading mood. This indicator is called the Average Directional Movement Index (ADX). It does not tell us if the market is rising or declining. It tells us only if the market is trending (either uptrend or downtrend) or trading. Having this information, we can use the suitable indicator in the right time.

The ADX is just one component of the Directional Movement Index (DMI). There are two other components: the +DI and the −DI. These two lines, when used together, tell us the direction of the market.

The DMI was invented by Welles Wilder and was described in his 1978 book, *New Concepts in Technical Trading Systems.*

So the DMI consists mainly of three indicators (or three lines): +DI, −DI, and ADX.

Both +DI and −DI show us the direction of the market (up or down), while the ADX tells us only if the market is in a trending mood or a trading mood. This means that if a downtrend is underway, the ADX will rise. The ADX declines when the market is witnessing a sideways period. Obviously, when the market is witnessing an uptrend, the ADX rises too.

Calculation

As we mentioned, the DMI has three lines: +DI, −DI, and ADX.

First we calculate the Directional Movement:

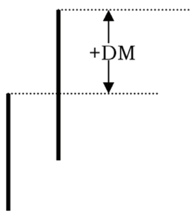
The Directional Movement is the largest part of today's trading range that is not included in yesterday's range. What does this mean?

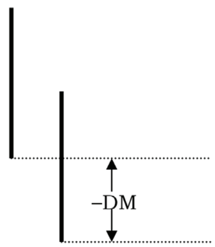
It means that 1) if today's bar is higher than yesterday's bar, we will subtract yesterday's high from today's high: (today's high − yesterday's high), and 2) if today's bar is lower than yesterday's bar, we will subtract the lows (today's low − yesterday's low). Note that we use positive values and no negative values in the calculation.

In the first case, we have +DM; in the second case the –DM is calculated.

In other words, +DM is the largest part of today's range which is outside yesterday's range during a rise.

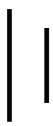
–DM is the largest part of today's range which is outside yesterday's range during a decline.





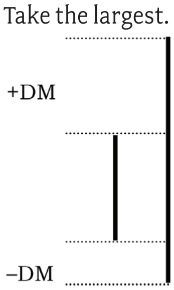
Notes:

1. An inside day will have a zero DM



Inside day, today's trading range is inside yesterday's range. DM = 0

2. During an outside day, we will have both a +DM and a –DM. Take the largest.



Outside day occurs when today's trading range engulfs yesterday's range. We have a +DM and a –DM. If +DM is larger than –DM, we will take it in our calculation and neglect the smaller –DM, and vice versa.

3. During an outside day, if +DM = –DM, then DM=0. This means that if the upper range is equal to the lower range, DM will be equal to zero, like the case of an inside day.

Now we calculate the +DM and –DM. +DM is the largest part of today's range that is not included in yesterday's range (during a rise). –DM is today's range that is not included in yesterday's range (during a decline). All values are positive. (+DM and –DM refer only to movement above or below yesterday's range.)

Next, we calculate the true range (TR):

The true range is the largest of the following:

1. the distance between today's high and today's low.
2. The distance between today's high and yesterday's close.
3. The distance between today's low and yesterday's close.

Each day we calculate the biggest of these three values and consider it as the true range (TR). Again, all values are positive.

Now we have calculated two things. First we calculated the Directional Movement, which can be +DM or –DM. Then we calculated the True Range.

Next, we calculate the Directional Indicator (DI):

Now we will calculate +DI and –DI. As we mentioned before, these are two of the three ingrediants of the Directional Movement Index.

+DI= +DM/TR

–DI= –DM/TR

So we divided the positive directional movement (+DM) by the true range to extract +DI. We also divide the negative directional movement by the true range to extract –DI.

+DI, as Welles Wilder explains, *is an expression of the percent of the true range that is UP for the day. –DI is an expression of the percent of the true range that is DOWN for the day. Obviously, +DI equals zero on a day that has no directional movement up; –DI equals zero on a day that has no directional movement down.*

Let us see some examples:

Example 1:

Yesterday's range was 19–21, while the close was 21. Today's range was 20.5–23.

Then +DM=2 and –DM=0.

TR will be the largest of the following:

1. The distance between today's high and low = 2.5
2. The distance between today's high and yesterday's close = 2
3. The distance between today's low and yesterday's close = 0.5

Then TR (true range) = 2.5

+DI = +DM/TR = 2/2.5= 0.8

What does +DI=0.8 mean? It means that 80% of the true range was up for this specific day.

Example 2:

Yesterday's range was 20–21.5, while the closing price was 20. Today's range was 18–20

Then –DM = 2 and +DM = 0.

TR will be the largest of the following:

1. The distance between today's high and low = 2
2. The distance between today's high and yesterday's close = 0
3. The distance between today's low and yesterday's close = 2

Then TR (true range) = 2

–DI = –DM/TR = 2/2 = 1

–DI = 1 in this example because today's range was outside yesterday's range.

So –DI = 1 means that 100% of the true range was down this specific day.

Some logic is needed before we continue explaining the calculation:

When we divide the directional movement by the true range to identify +DI or –DI, we actually see how the market moved in a certain direction compared to its range. This means that if there is direction in the market, the market is in a trend; DM will be high and might reach 1, (DM equals the true range). If the market is not showing a trend, DM will be low compared to the true range. Means that the market has no direction but is more in a sideways range.

For example, if yesterday's range was 25–27 and today's range was 25.5–27.25, the market rose, but there is no big move to the upside.

+DM will be equal to 0.25, while TR will be equal to 1.75.

+DI will then be equal to 0.25/1.75 = 0.14.

This example shows that the upward direction of the market is weak compared to the range of the day itself. (Only 14% of the true range was up.)

We average the +DI and −DI. Wilder used a default value of 14.

The proper way to do it is to first average +DM (14-day average of +DM) and we average TR (14-day average of TR). We then divide the averaged +DM by the average TR to calculate +DI.

We also average −DM (14-day average of −DM) and divide it by the average of TR (14-day average of TR) to calculate −DI

$+DI_{(14)} = +DM_{(14)}/TR_{(14)}$

$-DI_{(14)} = -DM_{(14)}/TR_{(14)}$

Averaging +DI, −DI, and TR can take different forms:

1. Welles Wilder used a summation function. He adds +DI for the previous 14 days and does the same with −DI and TR. He then divides the sums. He used a certain calculation to skip the tedious adding process. (Note that Wilder created this system before 1978, and during his days, there were no computers like today.)
   Today's $+DM_{14}$ = Previous $+DM_{14}$ − (Previous $+DM_{14}/14$) + Today's $+DM_1$
   Where Previous $+DM_{14}$ is the last calculation of $+DM_{14}$ (adding 14 days of +DM), and $+DM_1$ is today's +DM

So after the first summation, he uses this formula to calculate +DM, −DM, and TR for each new day.

2. The second way is to add the last 14 values, and each new day we drop the oldest value and add the new value. This will obviously be done with +DM, −DM, and TR. It's a simple summation process. If today's +DM=0, for example, we will add zero to the total and subtract the oldest value.

3. The third way is to take a 14-day moving average for the three components (+DM, −DM, and TR).

After the summation (averaging) process is done, we will calculate +DI by dividing the summed +DM by the summed TR. We will calculate −DI by dividing the summed −DM by the summed TR.

NOW: $+DI_{14}$ is the percentage of the total true range of the last 14 days that was up. $-DI_{14}$ is the percentage of the total true range of the last 14 days that was down. Both the DI_{14} and $-DI_{14}$ are positive numbers.

Logic: Let us say that the summed +DI = 25% and the summed −DI = 40%. This means that 25% of the true range for the past 14 days was up, while 40% of the true range during the same period was down. If we add these two figures, then 65% of the true range was directional (either up or down), and 35% of the true range was nondirectional. THUS, true directional movement is the difference between +DI and −DI. So, the more directional the movement of a certain stock, the greater the difference between +DI and −DI. Why? Each day we have a new +DM (market going up), +DI will increase while −DI will decline (because −DM will be zero). We add zero to the total and subtract the oldest value. If +DI and −DI get closer together, then the market is less directional and is moving sideways.

Now we calculate the ADX:

To calculate the ADX, we have to first take the absolute difference between +DI and −DI, and then we take their sum. Obviously we use the averaged +DI and −DI. (As we explained, we calculate either the averaged +DI or the summed +DI. The same holds true for −DI.)

1. Compute the difference between +DI and −DI,
DI diff = [(+DI) − (-DI)]

2. Compute the sum of +DI and −DI
DI sum = [(+DI) + (-DI)]

3. Calculate the directional movement index (DX)
DX = (DI diff) / (DI sum) *100

4. Calculate the ADX by taking a 14-day moving average of the DX.

ADX = 14-day moving average of DX

What did we do exactly?

We calculated the difference between +DI and −DI and calculated the sum of +DI and −DI. We then divided the difference by the sum to extract DX, and lastly, we calculated a 14-day moving average of the DX to calculate the ADX.

Note: This process is done with the averaged (summed) +DI and −DI.

In other words:

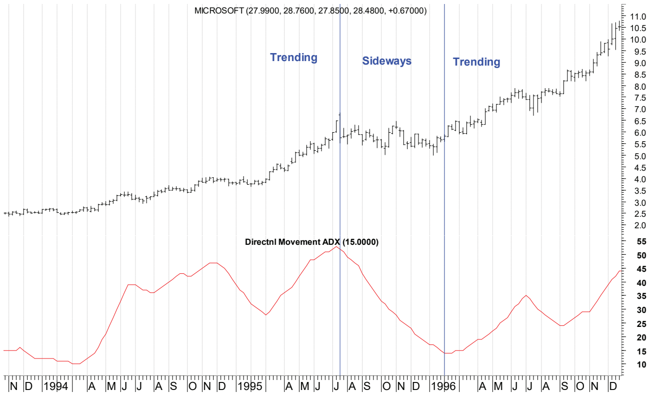
ADX = 14-day moving average of ([(+DI) − (−DI)] / [(+DI) + (−DI)]*100)

What does the ADX tell us?

It tells us, as Alexander Elder explains, that when the trend proceeds in a healthy manner, the spread between the two smoothed directional lines increases and ADX rises (meaning that the spread between +DI and −DI increases). ADX declines when a trend reverses or when a market enters a trading range.

So the +DI and −DI show us the market direction, when +DI crosses above −DI, the market is moving upwards. When −DI crosses above +DI, the market is moving downwards. The ADX itself does not show us the market direction. It only tells us that the market is in a trending period or trading period. This means that when the ADX is rising, there is a trend in the market (uptrend or downtrend). When the ADX declines, it tells us that the market is witnessing a sideways range.

WHY? Because the calculation of the ADX is based on the movements of +DI and −DI together. When they diverge from each other, ADX will rise, meaning that there is direction in the market, either up or down. When both +DI and −DI converge with each other, then the market has more horizontal movement than direction. **The greater the difference between +DI and −DI, the more directional or trending the market is (rising ADX).**



The chart above shows Microsoft along with ADX. As we can see during trending periods, ADX rises. During sideways ranges, ADX declines.

Using ADX alone

First, it is important to know that a rising ADX means that the market is witnessing a trend upward or downward. A declining ADX means that there is sideways action. ADX does not tell us the market direction. It only tells us if the market is trending or not. ADX oscillates in a range from 0 to 100 (remember that we multiplied the calculation by 100). In his book *Computer Analysis of the Futures Market,* Charles LeBeau mentions that ***as long as ADX is rising, any level of the ADX above 15 indicates a trend.*** He also recommends to use ADX with our favorite indicators, as each one will find certain levels and certain patterns in the ADX that will match our favorite indicators.

A rising ADX: A strong trend is underway and we should be using trend-following strategies. Moving average systems and breakout systems are preferred during these times when ADX is rising. Obviously, we cannot use stochastic and RSI as overbought/oversold oscillators. As we mentioned, during trending periods, oscillators stay for long periods of times in their overbought or oversold territories.

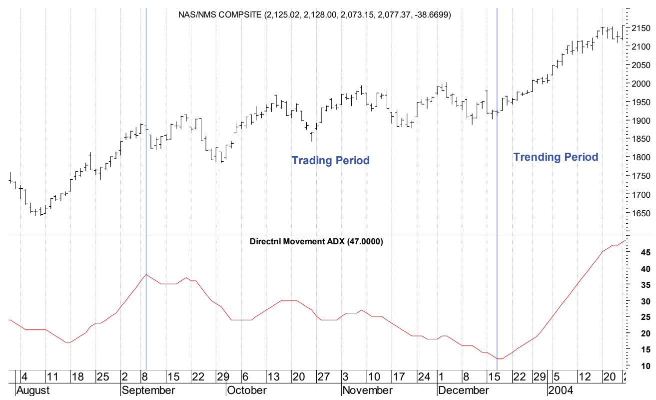
A rule of thumb: When the ADX is rising, do not use overbought/oversold oscillators to take signals contrary to the trend direction.

A falling ADX: We are witnessing a trendless market—sideways range. In this case, counter-trend strategies can be used. We can use oscillators to take signals contrary to the trend direction. We can use the stochastic and RSI as overbought/oversold oscillators, buying on dips and selling on rallies. Investors and fund managers who only use trend-following strategies do not take any actions when ADX is declining. They begin using their favorite trend-following indicators when ADX tells them to do so.

The major problem of the ADX: When an uptrend is underway, usually the ADX is rising. The problem lies when the trend reverses from up to down. The ADX will begin to fall, despite that the market is still trending. The only difference is that the market is now witnessing a downtrend instead of an uptrend. As we mentioned before, the ADX should be rising whether the trend is up or down. The problem with ADX lies during market reversals. As LeBeau explains it, *"the ADX will still be including the historical period of strong positive directional movement in its calculation, while inputting the new period of strong negative directional movement. As a result of the conflicting input, the ADX will begin to decline for a time until the old positive directional movement drops out of the data and the ADX begins to rise again because of the new downtrend."*

For this reason, ADX is better at triggering uptrends than triggering downtrends because bottoms usually take longer to build than tops. During a bottoming formation, prices will move sideways. The ADX will be declining. When a new trend begins, prices will move above their range, while ADX will rise. So ADX is very useful when a long sideways period divides a trend reversal.

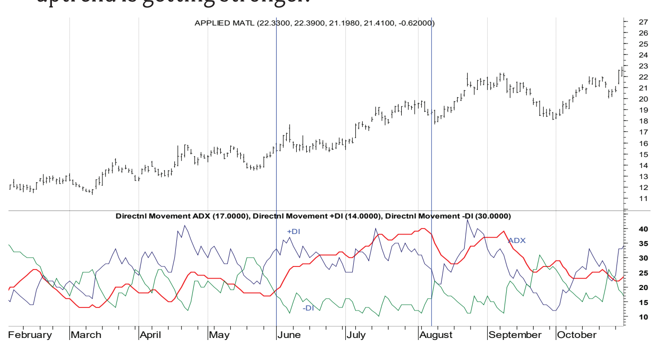
ADX will work best if we go from a downtrend to sideways to uptrend, or if we go from an uptrend to sideways to downtrend. In either of these cases, ADX will be much better than if the trend reversed suddenly from an uptrend to a downtrend, or from a downtrend to an uptrend.



Using ADX along with +DI and –DI

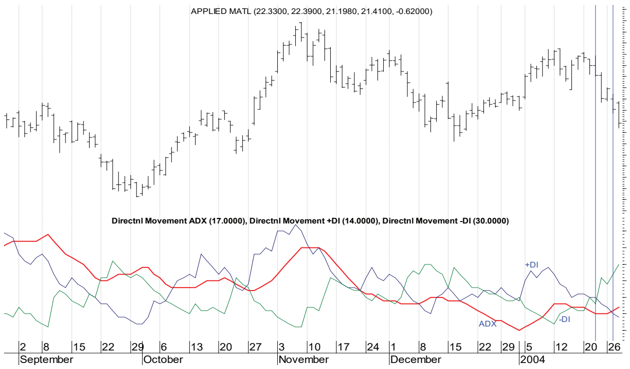
Some useful techniques can be used using ADX, +DI, and –DI.

1. BUY when +DI and ADX are above –DI and ADX is rising. Stop should be placed below the minor low. This shows that the uptrend is getting stronger.



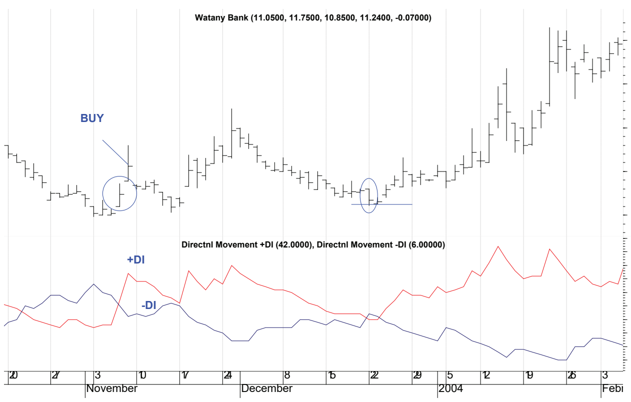
Applied Materials (AMAT) shows a buy signal during June 2003. +DI crossed –DI to the upside. ADX began to rise and crossed above –DI a few days later. This action is a hint that a trend began. If we look at the chart, we will find that before this buy signal, the stock was witnessing a sideways range. ADX, along with +DI and –DI, work very well when the stock moves from a trading range to a trend. Stops should be placed below the minor low.

2. Sell when –DI and ADX are above +DI and ADX rises. Place your stop above the minor peak. A downtrend is underway.



The first two techniques were explained by Dr. Alexander Elder in his book *Trading for a Living.*

3. Another technique explained by Wilder himself is worth mentioning. On the day that +DI crosses –DI to the upside, use the high of this day for entry points. If this high is broken, a buy signal is triggered. On the other hand, if –DI crosses above +DI, use the low of the crossover day as your key point. If this low is violated, a sell signal is triggered.



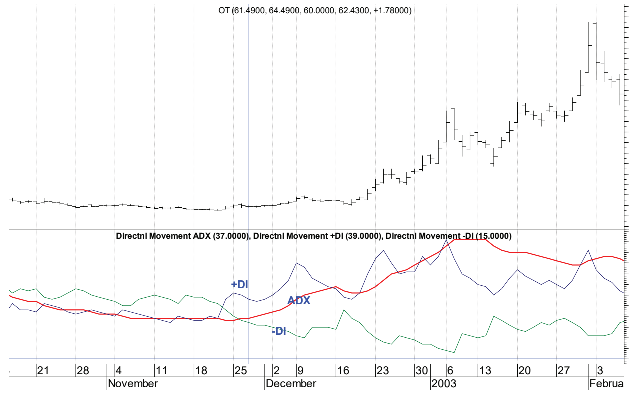
Watany Bank: During November 2003, +DI crossed above –DI. The second day the price crossed the high of the crossover day. A buy was triggered. The stock declined afterwards but did not break support. During mid-December, –DI crossed above +DI for only one day, but no sell was triggered. The low of the crossover day was safe.

4. When ADX is above both +DI and –DI, it means that the trend is overextended. Taking profits is recommended if ADX begins to turn down. My recommendation in this case will be to look at other indicators to see if the market is really overbought/oversold or not. Taking action will be better if based on price action (i.e., lower highs if the trend was up, or higher lows if the trend was down). Wilder suggested that if ADX is above both +DI and –DI, we should begin taking protective actions as soon as it begins to turn down.

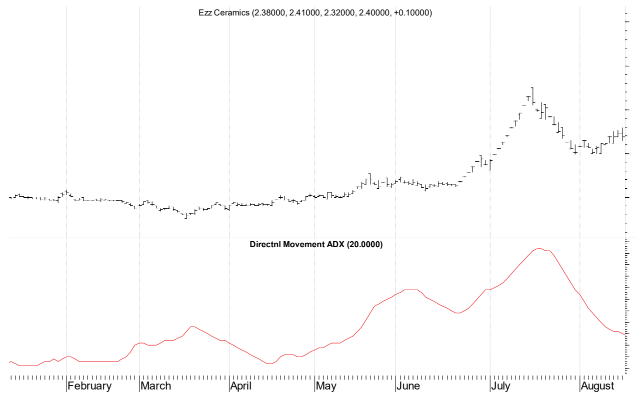
The logic of these techniques is as follows:

When +DI is above –DI, then the bulls are stronger than the bears. When ADX rises, it means that a trend is underway (uptrend as +DI crosses above –DI).

When –DI is above +DI, the bears are stronger. When ADX rises, it tells us that a new trend is underway (downtrend as –DI crosses above +DI).



In November 2002, while Orascom Telecom was trading below 8, +DI crossed above –DI. Few days later, ADX crossed above –DI and began to rise, signaling a buy signal. ADX told us that a new trend was underway very early. As we mentioned, ADX works beautifully with stocks that witness major bottoming formations.



Ezz Ceramics witnessed a trading range. Before the break of the major resistance at 1.5, ADX began to rise, hinting that a trend was underway. Look at how the ADX rose during May 2003, even before the major resistance at 1.5 was broken.

Different ADX calculation

We explained how Wilder calculated the ADX. He calculated +DM, –DM, and TR. He then took the sum of +DM, and divided it by the sum of TR to extract +DI. He also divided the sum of –DM by the sum of TR to extract –DI.

Some technicians use a different calculation. They divide the raw +DM by TR to extract +DI, and divide –DM by TR to extract –DI. After this process, they take a 14-day moving average of +DI and a 14-day moving average of –DI. So they divide the data first and then average the result afterwards.

Instead of averaging the components and then dividing, they first divide the components and then average the result. The numbers are probably different from Wilder's calculation, but we use the calculation that Wilder explained because it is the most credible one.

References

New Concepts in Technical Trading Systems: Welles Wilder.
Computer Analysis of the Futures Market: Charles LeBeau & David W. Lucas.
Trading for a Living: Dr. Alexander Elder.
Trading Systems and Methods: Perry Kaufman.

Quick Comments on the ADX

By Saleh Nasser, CMT, CFTe

As we know, the ADX is an indicator that tells us whether or not there is a trend. It is a trend identifyer. Welles Wilder was able to construct this indicator by defining moves; he defined an upward move and a downward move. By taking the high of today minus the high of the previous day during upward moves and the low minus the low during the downward days, he actually was able to solve 75% of the indicator.

The key here is comparing the number of days when the market moved up with the number of days when the market moved down, in addition to comparing the amplitude of these moves. In other words, he reached the secret recipe by reaching the conclusion that the market will be trending if the difference between upward moves and downward moves is expanding (in either direction), and the market will be non-trending if the difference between upward and downward movements is shrinking.

Thus, if we are rising, we will have a lot of +DMs and very few –DMs; if the market is declining, we will have a lot of –DMs and very few +DMs; thus, the difference between +DMs and –DMs expands either in the direction of +DM or the direction of –DM; taking the absolute difference between +DM and –DM (or +DI and –DI after normailizing them by the true range) will give you an indicator that will rise during an uptrend or during a downtrend, and will decline during sideways ranges.

On the left, we have five +DMs, one –DM, and four bars with no DMs. We can see that positive days are more than negative days and with a higher amplitude.

On the right, we have six –DMs, two +DMs, and two bars with no DMs. Here we have more negative directional movement.

Thus, the difference increases either to the positive side or to the negative side if there is an upward or downward movement. Taking the absolute difference will end up in an indicator that will rise whether the market is rising or falling.

We want to highlight the overbought and oversold conditions of the ADX.

This tactic is the most underrated technique in technical analysis, and did not have the importance it should have taken.

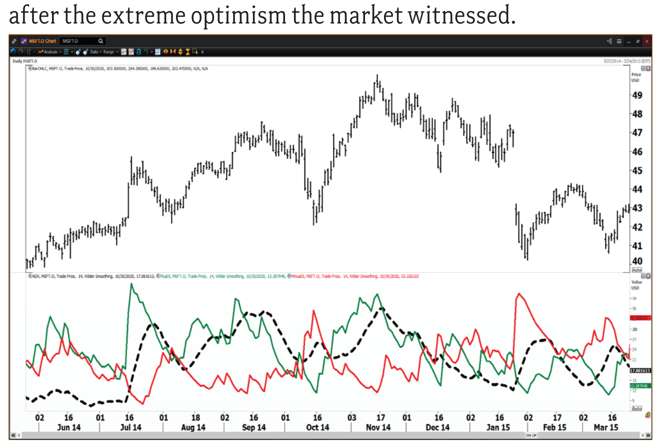
When we talk about the DMI overbought and oversold (ADX along with the +DI and –DI), we note that this system is the only system (as an indicator or set of indicators) that can depict a real overbought during an uptrend and a real oversold during a downtrend. What does that mean?

Overbought conditions that appear in oscillators that are in the direction of the major trend are considered as areas of strength rather than overbought. For example, during an uptrend, the stochastic will have most of its life in the overbought area. This is why we use trading tactics with the stochastic oscillator that enable us to buy at overbought when the rise is strong. We call this tactic the BOS system (buy on strength); we use both the stochastic and MACD, and we actually buy as the stochastic approaches overbought or is actually inside overbought territory. The same goes for the RSI and other oscillators, including the CCI and others.

The DMI system, however, is able (sometimes) to depict overbought conditions during strong trends. This is an almost impossible job for an indicator to do, but the DMI system can do it. The reason why the DMI system depicts overbought situations during uptrends and oversold during downtrends is a bit sophistcated cause it includes a thorough understanding of crowd psychology and how peaks and bottoms form. But let us explain it in a simple way.

When the ADX is above the +DI during an uptrend and both the ADX and +DI are at high levels (i.e., 40 and above), the difference between both +DM and –DM is bigger than +DM itself, meaning not only that the market is witnessing strong rises (i.e., buyers are getting stronger), but also that –DM is getting much smaller (i.e., sellers are getting much weaker). This takes us to the extreme level of optimism when buyers get much stronger and sellers become almost nonexistent. This what happens when the difference between +DM and –DM is bigger than +DM itself (because the difference takes into account –DM too).

Having an ADX that surpasses the +DI at high levels means that sellers are getting weaker and weaker while buyers are getting stronger and stronger; when the ADX begins to flatten at these high levels, this is when we say "catch overbought!!!" because this flattening is the first sign of potential weakness after the extreme optimism the market witnessed.

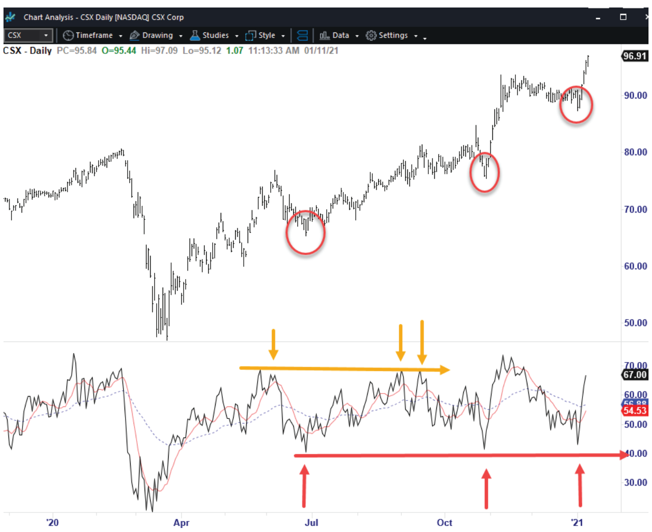


Technical Analysis for the Trading Professional—"Oscillators Do Not Travel Between 0 and 100"

By Connie Brown, CFTe, MFTA

It is always helpful to see concepts within a book applied to a current chart. It shows that the approach remains valid and timeless. In this case study, we will look at a railway stock with a 14-period RSI to study the oscillator character described in the chapter "Oscillators Do Not Travel Between 0 and 100." *Technical Analysis for the Trading Professional* was first published in 1996 and then revised in 2011. The book was once required reading for CMT III. It is now part of the IFTA CFTe syllabus.

Figure 1. CSX Corporation (Railroad) — Daily Bar Chart with a 14-period RSI. The oscillator has a simple 9-period (red) and exponential 45-period (blue) moving average.



CSX in Figure 1 is a daily chart providing a current view as of January 11, 2021. A 14-period RSI forms bullish entry signals when the RSI found support near 40. Focus on the range of travel in the RSI (black line). RSI declines toward the 40 level into the end of June 2020. The RSI creates a horizontal level of support at 41-42 in CSX five times. Two of the five may be difficult for you to detect for the moment.

You cannot change this chart to look at a different stock and think the ranges created in CSX will apply to the new stock. Each market creates a well-defined level that repeats but only fits that data set. A stock that favors RSI support at 46 is not a miss because it does not use 41 like CSX in Figure 1.

Always study horizontal amplitude levels that repeat. We are not looking at any diagonal lines that connect pivots as a trend line. Every stock or market will have a unique character, but the range guidelines will not change. Bear markets tend to fail near RSI 65-68 and then fall towards 20 to 30. Bull markets hold RSI 40 to 46 and then push upwards toward 80 or 90. It is therefore critical to read your chart and not just memorize a rule. As I tend to keep permanent charts of stocks in like sectors, I do not use the same chart workbooks to view multiple symbols. Therefore, the analytics remain a fixed record. Treat each chart's time horizon, such as daily, weekly, or monthly charts, as independent studies. Each will create its own clear repeating level of support and resistance on a horizontal axis by RSI.

In Figure 1, each RSI test near the 40 level became an opportunity to buy CSX stock in 2020. Figure 2 shows the first test near 41 in December 2019. It is marked on the far left side of the Figure 2 chart. Such a signal is often overlooked and one you may have missed when I stated there were five signals at this oscillator displacement. But this first signal is extremely important. It is important because the RSI pivot preceded the sharp break to follow when RSI plummeted to new extreme lows. This level of support prior to a shock is nearly always retested after a shock extreme.

Figure 2. CSX Corporation (Railroad) — Daily

Most will overlook the strongest signal in the chart of the five tests near the 41 level. It is the retest signal at RSI 41 that occurs in April 2020. Not only is this the retest of the December 2019 pivot, but it occurs at the crossover of its own two averages where the short period average is crossing up through the slower moving average. This signal is much stronger than the conventional divergences we learn about in our basic training. These mid-range signals at support or resistance are more subtle and often mark the true launch of a major trend or swing. Often, the juxtaposition of RSI and its crossing averages mark the start of wave 'iii' within a developing swing. This is what differentiates the skilled technician from an average practitioner. It is always about attention to the details. Does the price action cause the RSI to often form a "W" pattern at the horizontal support or resistance zone? Or is the character like CSX defining a sharp RSI 'V' pattern off support? Does the oscillator form 'V' bottoms but 'M' tops into resistance? The market will show you how it wants to work if you look closely. This is how to develop a probability for the signal forming. If the market respected the horizontal level several times in the past, it will likely be a true signal when it appears the next time within this target zone. If it often fails at a repeating horizontal zone; you have your warning not to trust it this time either. Oscillators can indicate a probability.

The price data set will give you a clear picture of how it moves the RSI into a reversal signal in both tops and bottoms. Let the market guide you rather than putting yourself in a position to go out on a hunt for a preconceived expectation. The more you expect, the less you will see within your chart.

In Figure 1 a horizontal line of resistance is marked in RSI with caution arrows pointing down at the resistance zone near 68. The 65-68 level is often the retracement target for RSI in a correcting bear market. While each pullback showed support near the bullish 40 level, the repeating failures near 68-70 should raise a concern that requires further examination.

Figure 3. CSX Corporation (Railroad) — Monthly Equivolume Chart

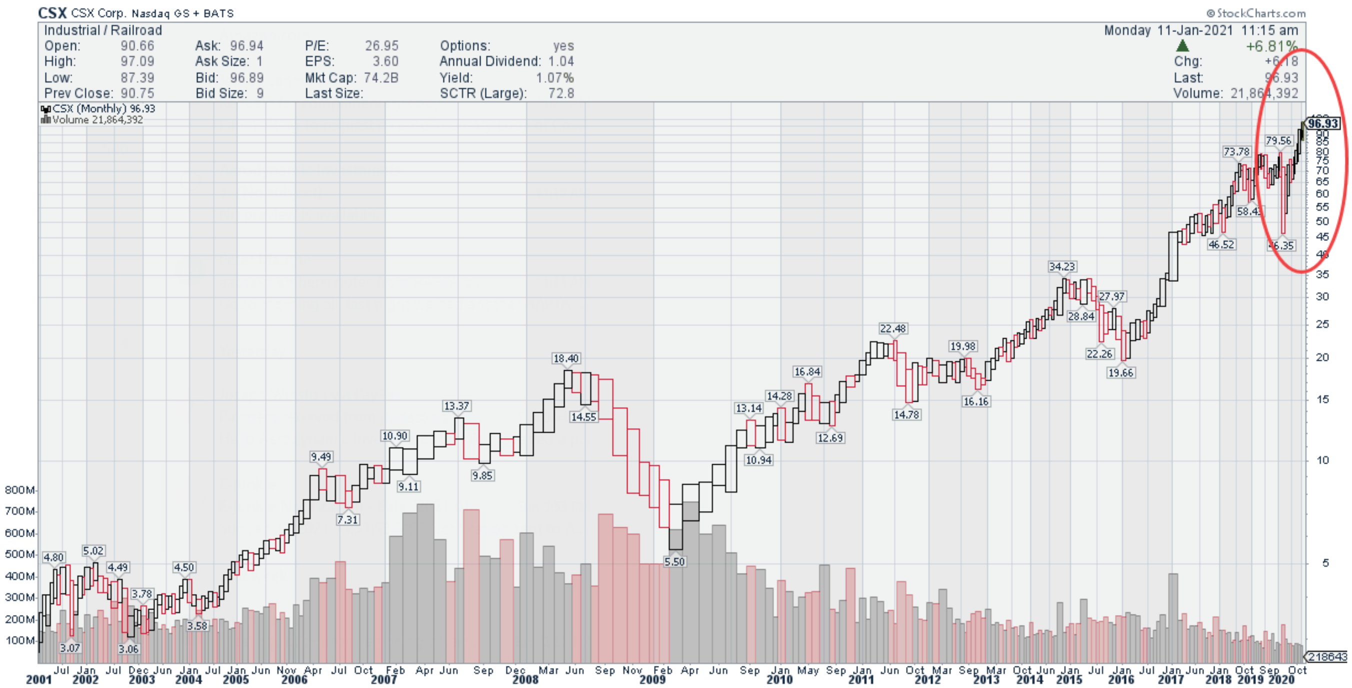


Figure 3 is a monthly chart of CSX Corporation showing prices up to January 11, 2021. Rather than viewing the price action in a bar chart, an Equivolume chart is plotted. This gives an opportunity to show you a charting method underutilized. On the bottom of the chart are bars displaying volume. They are conventional, but the volume width looks odd, as they have to mark the same time interval as the bars in prices that are not conventional. The chart shows a steady trending decline in volume since 2017 without much more information. An Equivolume chart shows the price range of the period like a bar chart, but the width of the bar reflects volume during this period. The wider the bar, the more volume contained within the period—in this case per month. It is easy to spot wave 'iii's' and strongest swings. The circled price action in Figure 3, containing the current rally since the March 2020 low, shows progressively narrowing bars of diminishing volume. Not only are the bars narrow in the current swing, but they are compressing and show weaker participation relative to the character within any prior swing in the chart. The RSI range failing often near 68 is providing us with a warning. The volume within the rally is waning as is befitting a fifth wave position.

Equivolume does not show the open and closing price, but this is not how we are using this chart style. Compare the series of bar widths within the duration of each swing. The more you study volume charting techniques with RSI, the quicker you will realize you are reading volume within RSI itself. Volume additions to your chart soon become unnecessary. Not that you are ignoring volume, but you are reading volume within the oscillator position, and the ranges it is traveling carry more information than a novice will read from the indicator.

One last takeaway for clarification as it is extremely important: A chart that makes an extreme RSI low in a shock environment will rise and then test the RSI amplitude of the oscillator low *behind or prior to the extreme displacement.* If you study Figure 2, CSX made such a test. It is this amplitude test at the same level before and after the extreme pulse down in RSI that is often the safest entry in a new trend after the shock. However, be aware of the environment and range the oscillator travels after the test. It may carry an early warning that the trend is not as healthy as one would like to believe.

Author Profiles

Michael A. Gayed, CFA

Michael A. Gayed is portfolio manager of the ATAC Fund Family at Toroso Investments, an investment management company specializing in ETF focused research, investment strategies, and services designed for financial advisors, RIAs, family offices, and investment managers. Prior to Toroso Investments, Michael was the co-portfolio manager and chief investment strategist at Pension Partners, LLC, an investment advisor managing mutual funds and separate accounts.

Michael is the author of five award-winning research papers on market anomalies and investing. He was an active contributor to MarketWatch for a number of years and has been interviewed on CNBC, Bloomberg, and Fox Business as well as the *Wall Street Journal* Live for his unique approach to interpreting market movements.

Michael earned his B.S. with a double major in finance and management at New York University Stern School of Business. He became a CFA Charterholder in 2008.

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Carlos Jaureguízar, Ph.D., is the CEO of Robexia AI TechConsulting, an artificial intelligence laboratory specialized in several sectors, with a focus on finance and advertising through machine learning. Carlos previously worked in the BBVA Treasury Department and has held positions on the IFTA board and as IEATEC chairman. He currently participates in IEATEC's Committee for the Transition to Artificial Intelligence. Carlos holds a degree in economics (UAM), a master's in financial markets (UAM), and is certified ACI FX and MM Level I. In addition, he passed the DEA exam with a Black-Litterman inverse optimization model dissertation and received a Ph.D. in applied economy with a merit with distinction grade, cum laude, after the defense of the thesis: "To what extent do the candlestick patterns anticipate the continuation or turn of the previous trend of quoted prices?"

In addition to authoring numerous articles and actively participating in forums and conferences, Carlos has written two trading books: *High Profitability in the Stock Market and Other Financial Markets* and *Candlestick for Traders.* Carlos is the founder of Noesis, Robexia, and Finavid and a founding partner of Contacto, an advertising agency, and Aquinas American School.

Regina Meani, CFTe

Regina Meani, CFTe, covered world markets as a technical analyst and associate director for Deutsche Bank prior to freelancing. She is an author in the area of technical analysis and is a sought after presenter both internationally and locally, lecturing for various financial bodies and universities as well as the Australian Stock Exchange. Regina is a founding member and former president of the Australian Professional Technical Analysts and a past IFTA Journal director, 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 and has belonged to the Society of Technical Analysts, UK (STA) for over 30 years.

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Sandra Nieto is COO of Robexia Tech Consulting, an artificial intelligence laboratory for the financial and advertising sector. Previously, she worked first as a senior analyst and later as an account executive for Noesis SL, dedicated to the design and development of financial products, services, and projects. Sandra has a degree in mass communication (UMA) and specialized in marketing and advertising (UCM). Working for the financial sector, she developed an interest in technical analysis, which allowed her to participate in several published articles dedicated to the subject. She's currently a member of the IEATEC's Artificial Intelligence Committee, dedicated to introducing new AI models and possibilities for the study of this sector.

Shinji Okada, CMTA, CFTe, MFTA

Shinji Okada majored in political science at Nihon University Graduate School of Law and after graduation, started his business career at Securities Japan Co. Ltd., Tokyo, where he engaged in the sales of various securities (e.g., Japanese/U.S. equities, fixed income and investment trusts), through which he became interested in the practical applications of technical analysis. As his interest in technical analysis grew, he learned that so many investors tended to sustain losses panicking at various trend turning points. It is this experience that has drawn him to the research of the regression analysis of trends to find their turning points, making the best use of famous technical analysis tools (e.g., Dow Theory, Elliot Wave Theory, Bollinger Bands). In March 2020, he joined QUICK Corp. and has mainly been engaged in planning and providing new and better information services to financial institutions while continuing his research in technical analysis.

Dr. Oliver Reiss, CFTe, MFTA

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

As a private investor, Oliver 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 Oliver 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's conferences, he also presented the results of his MFTA research at the IFTA Conference in Cairo. In the current paper, Oliver continues his research on the Empirical Mode Decomposition and presents its application for trading on shorter time frames.

Christoph T. Wildensee, Ph.D., MFTA

Christoph Wildensee has a Ph.D. in business administration. He is a well-known auditor and data/process analyst at enercity AG in Hannover, Germany. Christoph's special focus is on finding errors and optimization potential in IT systems relevant to accounting, including, in particular, the Energy Trade and Risk Management (ETRM) system, which is used to handle all energy trading activities at enercity. He was also a member of the team evaluating the new Pioneer/Hitachi-ABB ETRM system.

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