

How to predict a turning point for stocks and shares – An alternative approach

In the previous paper entitled “How to predict a turning point for stocks and shares – A classic approach,” we explored the possibility of predicting a turning point in the movements of stocks and shares. The approach we took was a mainstream analysts’ approach and the results were useful, but not compelling. This paper is exploring an alternative approach based on statistics.

In case you have not read the first paper, a turning point in stocks, sometimes also known as an inflection point or pivot point, is a moment when a significant change in the direction of the stock movements takes place.

We also know that this turning point becomes obvious only after we look at the past and we can clearly see the point where this change happened. The difficulty is that often the values change direction, but then for a while, they keep on oscillating up and/or down, before definitely setting the new upward or downward trend. The trick is to predict a genuine turning point, as opposed to just one of these irregular ups and downs.

When we use the word prediction, we do not mean predicting future turning points. This would be a bridge too far. What we mean is predicting, in this moment of time, that the turning point is actually taking place. You check your stocks, and you conclude that the stocks are likely to start a downward or upward run. This enables you to take action, which is to sell, buy, or whatever else is on your mind.

To demonstrate this alternative approach, just like in the previous paper, we will use the actual stock exchange data. To explain the method, we’ll use the GSK closing stock values. The time horizon and the length will vary, depending on what we are trying to explain. Let’s start with the philosophy first.

A very intuitive way of thinking is that if today’s stock value is above or below some historical value, then this potentially indicates a change in direction. The question is what should these historical values be, and how should we measure deviations from them?

One possibility is to use just the last five daily closing stock values (five, because a week has five trading days) and take their average value. This could then be the basis for deciding in which direction the current daily stocks are moving. If today’s value is higher than the last five days’ average, then we have a potential move upwards. If it is lower than the five-day average, then we have a potential move downwards.

We’ll take a look at GSK data from 1 September 2022 until 31 May 2023 to see if this could be a valid way of thinking. In total 187 trading days. Below in Fig 1, we show just the first 9 and the last 5 rows of data.

Column C is calculated as a 5-day moving average using a formula =AVERAGE(B2:B6) for cell C7, which was then copied down. We have effectively created a time series of 5-day moving averages.

	A	B	C	D	E	F	G	H	I	J
1	Date	GSK Close	5MA	Diff	UL	LL				
2	01/09/2022	1357.20						0.36	Overall mean	
3	02/09/2022	1352.00						24.74244	Overall SD	
4	05/09/2022	1357.80						1	L	
5	06/09/2022	1347.40								
6	07/09/2022	1344.40								
7	08/09/2022	1344.20	1351.76	-7.56	25.09893	-24.386				
8	09/09/2022	1348.60	1349.16	-0.56	25.09893	-24.386				
9	12/09/2022	1377.60	1348.48	29.12	25.09893	-24.386				
10	13/09/2022	1359.40	1352.44	6.96	25.09893	-24.386				
184	24/05/2023	1408.80	1429.20	-20.40	25.09893	-24.386				
185	25/05/2023	1384.60	1422.48	-37.88	25.09893	-24.386				
186	26/05/2023	1392.20	1414.64	-22.44	25.09893	-24.386				
187	30/05/2023	1371.00	1408.32	-37.32	25.09893	-24.386				
188	31/05/2023	1346.40	1397.36	-50.96	25.09893	-24.386				
189			=AVERAGE(B183:B187)							
190			=B188-C188							
191					=H\$2+H\$4*H\$3					
192						=H\$2-H\$4*H\$3				

Fig 1. Calculating differences between closing values and previous five-day moving averages

A formula for moving averages, at least for this purpose, is:

$$\bar{y}_t = \frac{y_{t-m} + y_{t-m+1} + y_{t-m+2} + y_{t-m+3} + y_{t-m+4}}{5} \quad (1)$$

This can be written in a more compact form as:

$$\bar{y}_t = \frac{\sum_{i=t-m}^{t-1} y_i}{m} \quad (2)$$

Where,

\bar{y}_t = Moving average

y_t = Data points

n = Total number of data points

m = Number of moving averages (in our case 5)

t = Specific value at time t, and it goes from t = m + 1 ... n (in our case from t = 6 ... 25)

So, the first 3 moving averages, for example, are:

$$\bar{y}_6 = \frac{y_5 + y_4 + y_3 + y_2 + y_1}{5}$$

$$\bar{y}_7 = \frac{y_6 + y_5 + y_4 + y_3 + y_2}{5}$$

$$\bar{y}_8 = \frac{y_7 + y_6 + y_5 + y_4 + y_3}{5}$$

D7 cell contains a difference between the daily closing value and the previous five-day average. The formula in cell D7 is =B7-C7 and it is also copied down. We'll explain the other columns and cells shortly.

The GSK stocks from this period, shown as a line graph, are depicted in Fig 2.



Fig 2. GSK closing values and approximate trend lines covering the runs between the turning points

We provisionally inserted red lines that represent short stock runs, or local trends. There are 9 of them and where they intersect we potentially have a turning point. We can see 8 potential turning points.

Let's now show the graph of the column D, i.e. the differences between the closing values and the rolling previous 5-day averages. The graph is in Fig 3, and it shows that the differences are a proper stationary time series. We have also calculated the Upper and Lower limits by calculating the mean and the standard deviation for this series of differences. These values are given in Fig 1 in cells H2 and H3 respectively, using the formulae =AVERAGE(D7:D254) and =STDEV.S(D7:D254).

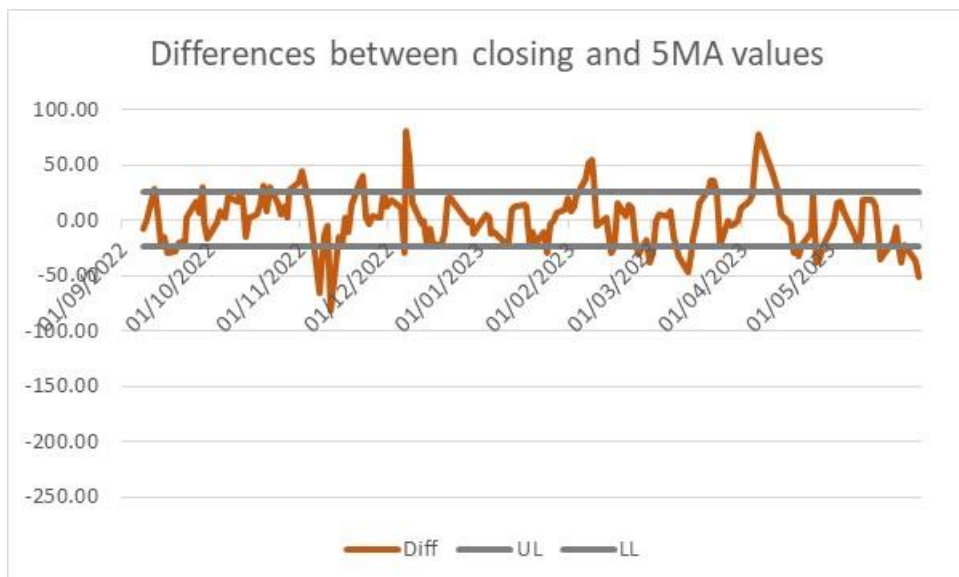


Fig 3. Differences between closing values and moving averages with the limit lines

The Upper Limit and Lower Limit are calculated using the equation:

$$\bar{y}_D \pm L \sigma_D \quad (3)$$

Where,

\bar{y}_D = The mean value of all the differences between the actual prices and the past five observations' moving average

σ_D = Standard deviation of all the differences

L = Number of standard deviations

The Upper Limit is the expression where we add $L \times \sigma_D$ to \bar{y}_D and the Lower Limit is where we subtract $L \times \sigma_D$ from \bar{y}_D . These two lines are columns E and F from Fig 1. The value of L also comes from cell H4 in Fig 1.

One possible line of reasoning could be that if a difference “sticks out” above or below the limits (UL and LL), then we have a clear indication that the trend has changed, and we have a turning point. Fig 4 depicts this reasoning.

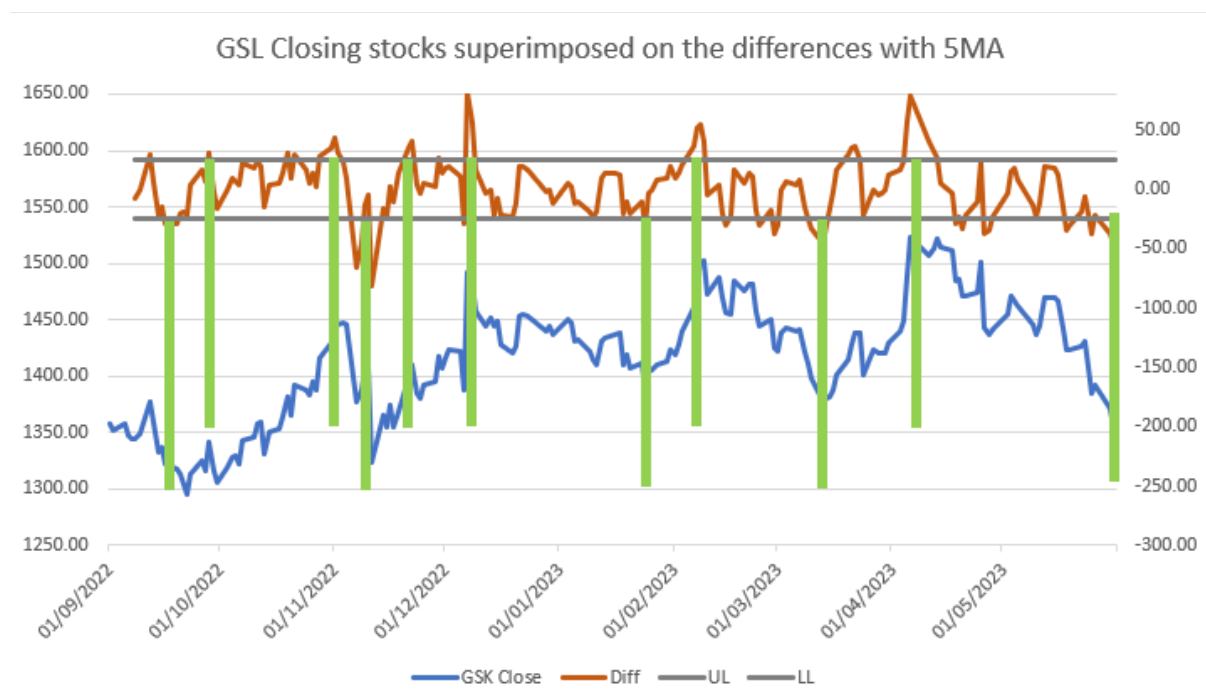


Fig 4. Closing stock values superimposed on differences between the closing values and moving averages with the potential turning points marked with green vertical bars

In Fig 4 we superimposed on the same graph, using the secondary axis, several key columns from Fig 1. The blue line represents the closing values of GSK stocks (column B). On the secondary axis, we have the differences between these closing values and their 5-day moving average (column D) as brown line, as well as the Upper Limit UL (column E) and Lower Limit LL (column F), both grey lines.

We can see that when the brown line (the differences) sticks above or below the two grey lines, at the same place it appears that the blue line is experiencing a turning point. To emphasize this, we have in a few most obvious places manually added green vertical bars. They indicate the turning points. We might be onto something.

OK, this is the philosophy of the method and a couple of experimental indications that the method might work. Let's put the implementation details together and see if it really works. However, before that, I would just like to address the issue of what defines a turning point.

I experimented with lots of data sets and concluded that the length of the series would determine what is considered to be a turning point. This is like looking at a daily chart with all the ups and downs, but when you take a monthly chart, for example, these daily trend variations are insignificant in the context of monthly, or yearly data. In other words, what might appear to be a turning point on a daily or a weekly chart, will not necessarily be the case on monthly or yearly data.

This reminds me of the problem called “How long is the coast of Britain?”. Benoit Mandelbrot came up with a solution that it is virtually infinite, assuming you use an infinitesimally small yardstick. We have exactly the same challenge here. If you zoom out, what might appear as a change point, is only a temporary setback in the longer upwards or downwards run. Anyway, we’ll return to this aspect once we unpacked the method.

To demonstrate how this line of thinking was implemented as a method, we’ll again use GSK closing stock values, but over a period of only 41 trading days from 1 March 2023 until 28 April 2023. Fig 5 below shows the spreadsheet we used to implement this method. We are showing only the first 8 and the last 5 rows.

	A	B	C	D	E	F	G	H	I	J	K
1	Date	GSK	SMA	UL	LL	IF	Clean	Turn			
2	01/03/2023	1422.00								L =	1
3	02/03/2023	1438.80									
4	03/03/2023	1442.20									
5	06/03/2023	1439.40									
6	07/03/2023	1441.80									
7	08/03/2023	1422.40	1437	1445.27	1428.41	Change DOWN	Change DOWN	1,422.40			
8	09/03/2023	1412.20	1437	1445.17	1428.67	Change DOWN					
9	10/03/2023	1398.60	1432	1445.19	1418.01	Change DOWN					
38	24/04/2023	1474.00	1485	1501.39	1468.05	Change DOWN					
39	25/04/2023	1500.20	1477	1484.36	1469.96	Change UP	Change UP	1,500.20			
40	26/04/2023	1442.20	1480	1493.04	1467.76	Change DOWN	Change DOWN	1,442.20			
41	27/04/2023	1437.00	1472	1492.23	1451.13	Change DOWN					
42	28/04/2023	1441.00	1465	1490.72	1439.12	Change DOWN					
43			=AVERAGE(B37:B41)								
44				=AVERAGE(B37:B41)+\$K\$2*STDEV.S(B37:B41)							
45					=AVERAGE(B37:B41)-\$K\$2*STDEV.S(B37:B41)						
46						=IF(B42>D42,"Change UP",IF(B42<E42,"Change DOWN",F41))					
47							=IF(F42=F41,"",F42)				
48								=IF(G42<>"",B42,"")			

Fig 5. A method of calculating the turning point in stocks and shares

Rows 43:48 in Fig 5 contain the details of how the last row 42 was calculated. The same formulae apply to all other rows in columns B:H. Let’s unpack this.

Column C in Fig 5 remains the same as before, i.e. we just calculated the previous 5-day moving averages.

Columns D and E contain the Upper Limit (UL) and Lower Limit (LL) values, but they were calculated a bit differently than before. To calculate both limits, we are using the average of every 5-day moving period, as well as its standard deviation. This makes these two statistics dynamic and changing as the moving averages change. The value of L, which is the number of standard deviations, is given in cell K2, and we are using just 1 standard deviation.

Column F in Fig 5 has an IF statement that reads for cell F7: =IF(B7>D7,"Change UP",IF(B7<E7,"Change DOWN",F6)). It says that if the actual closing value is above the Upper Limit, then insert the label “Change UP”. If it is below the Lower Limit, then insert “Change DOWN”.

As column F generates too many labels, which correctly return the IF statement, to reduce the number of labels, we introduced column G in Fig 5. In the last cell of this column, we use a simple

statement: $=IF(F42=F41, "", F42)$. In other words, if the previous cell already contains the same label, we avoid repeating it.

The final column H in Fig 5 just returns the value of the stock for that day, providing that there is some content, i.e. a label, in column G. This value is a turning point. Let's see how this looks as a chart. Fig 6 provides a visual.



Fig 6. Turning points identified on the stock movement chart

The vertical bars represent the cells H7, H14, ..., H40 from Fig 5. In other words, where we identified a turning point using this method, the value of the stock is represented by a vertical bar. Just for the purposes of this tutorial, we coloured the bars in two different colours. Red when the turning point indicates that the shares will go down, and green when the turning point indicates that they will go up.

By just looking at the chart in Fig 6 we can conclude that the method identified the turning points fairly well. There is a bit of a lag to flag the turning point, but this is to be expected, given that we do not want to react to every irregular and temporary change in direction.

To complete the validation, let's take just a bit longer time series. We'll stick to GSK, but this time we'll use the period from 12 July 2023 until 14 November 2023. In total 90 trading days with the corresponding closing values. Fig 7 shows the two versions of the same method, but with one difference. The graph on the left uses $L=1$ and the graph on the right uses $L=2$.



Fig 7. Turning points identified for $L=1$ on the left and $L=2$ on the right

We can see that $L=2$ produces fewer turning points. If we used a longer time series, this would have been even more obvious. The number of standard deviations used to define the Upper and Lower Limits acts as a “yardstick” with which we measure deviations.

This takes us back to “How long is the coast of Britain” and how the end result depends on the size of a yardstick, at least metaphorically. For longer data sets you need a larger yardstick (in our case, $L=2$), and for shorter data sets you need a finer yardstick (in our case, $L=1$).

In conclusion, this method seems to be a good proxy for identifying, in real-time, if a turning point has just occurred and if the stock data are about to start following a new trend. The approach requires some finessing to decide how sensitive the system should be concerning the value of the standard deviation, which determines the Upper and Lower Limit sensitivities.

Like with any other method, especially when it comes to the stock exchange data, we’ll never get the outcome 100% right, but this seems to be as close as we can get to predicting if the turning point has just happened.

As a closing remark, I experimented with numerous ways to detect turning points. I went down the path of deploying exponentially weighted moving averages (EWMA), CUSUM and a number of other methods, but in the end I returned to this simple moving average approach. All these other methods were just adding complexity and, although they sound sophisticated, the results were not as good as using simple moving averages. Hope you find it useful.

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