Probability Predictions of Currency Movements: Judgement and Technical Analysis

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INTRODUCTION
For the effective use of technical analysis in the volatile environment of the world’s financial markets, it is important to realise:

1. the critical role played by human judgement, and
2. the need to enhance the analyst’s ability to express this judgement in a probabilistic form.

Chartist techniques, which form the basis for technical analysis, are effectively based on human judgement. Currency movements are heavily influenced by prevailing market sentiments that manifest themselves via varying levels of optimism, pessimism and differing degrees of uncertainty in the minds of market participants. It is this mindset that the Chartist approach aims to capture by examining patterns in the time path of exchange rates. The efficient use of judgement in extracting information from the plethora of pattern swings and volume spikes requires not only an interpretation of the predicted movement (direction of change) but also an associated probability assessment (probability of a rise or fall) which accompanies the prediction. There is, therefore, a need for technical analysis techniques to express financial price movements in a probabilistic form. This can be achieved by calculating moving period estimated probabilities (EPs) from first differences in the logarithms over a specified period. EPs are based on the assumption that for a short number of data points (e.g., less than 50 days for daily data) the changes in the logarithms of currency series will be approximately Normally distributed with a stable mean and standard deviation. Over a longer range of data points, however, the distribution can be subject to changing means and standard deviations due to the influences of optimism, pessimism and uncertainty. In contrast to simple directional predictions or buy and sell statements, probability statements convey much more comprehensive and effective information to the user.

Probability statements, provided by analysts, need to be made in a framework that incorporates information on the nature and characteristics of exchange rate series. There are several issues that need to be considered in relation to the making of probability statements regarding currency movements. It is necessary to have a clear structure in the formation of probability statements, that is, to have a clear and appropriate statistical distribution in mind and to be able to form statements regarding the relevant parameters of the distribution. It is also necessary that, when the resulting probability statements have been formed, procedures are available to evaluate the accuracy and validity of probability predictions at the end of the predictive horizon. This provides valuable feedback that can be used to improve future probability predictions. EPs provide a natural method on which an analyst can base his/her judgemental probability predictions in a form that is consistent with the framework. These issues are examined below.

TECHNICAL ANALYSIS AND THE ROLE OF JUDGEMENT
There are two distinct aspects of technical analysis: the traditional chartist approach and mechanical technical analysis. The effective application of human judgement in a technical analysis context requires a clear understanding of the distinction between the two approaches.

The chartist approach examines market action, primarily with the use of price charts, in order to predict future price trends. Chartists see the market price as encompassing all aspects of the market, and balancing all the forces of supply and demand. The chartist approach is subjective and its effective use depends on the skill of the individual chartist. As such, charting is often described as an art rather than a science. Its effective use, therefore, depends heavily on the quality of the analyst’s judgement.

Mechanical technical analysis, on the other hand, attempts to apply the chartist principles by using statistical analysis to quantify aspects of the chartist approach. This approach essentially attempts to convert the subjective principles of the chartist approach into quantitative indicators that can be mechanically used to signal buy and sell decisions. In practice, however, decision making is usually not that simple and the effective use of mechanical technical analysis requires a choice between a number of different indicators as well as input from traditional chartist approaches. Technical analysis as a tool for predicting financial price movements is heavily influenced by the analyst’s judgement.

There are various problems associated with evaluating technical analysis techniques in practice. The appraisal of chartist techniques is difficult given their highly diverse and subjective nature. The chartist approach involves the subjective interpretation of financial price behaviour based on the underlying views of market psychology. There is, therefore, no direct method of evaluating individual aspects of the chartist technique, as the approach is holistic. It is only possible to examine the judgement of the individuals using the techniques via an examination of the realised financial price values after predictions have been made.

Mechanical technical analysis would, however, appear much easier to evaluate as the specific procedures are statistically defined. The problem, however, even in evaluating these techniques, is that there exists an element of judgemental interpretation as in the chartist approach. Mechanical technical analysis should be viewed as a guide to decision making and not as providing definitive answers.

Technical analysis can provide clear buy and sell signals and convey information about the confidence in such signals. But how can an analyst express this confidence? A probability statement with the directional prediction (e.g., the probability that a specific currency will have risen by the end of a 5-day period) provides this measure and conveys more comprehensive and useful information to the user than the directional statement alone. This is because the probability statement explicitly communicates the embedded uncertainty. This uncertainty reflects the degree of predictability and volatility in the market. Probability predictions are, however, more difficult to form than simple predictions of directional change.

ESTIMATED PROBABILITIES, PROBABILITY PREDICTIONS AND THE STATISTICAL DISTRIBUTION OF CURRENCY MOVEMENTS
When directional probability predictions are made, the evaluating framework should provide a mechanism whereby information concerning the nature of currency movements can be incorporated. Keren’s (1991) work suggests that analysts should be guided into using the appropriate distribution when making their predictions. The distribution should reflect the series that is being predicted. In the case of currency movements as well as movements of most financial series, it is appropriate to consider the changes (first differences) in the series from one data point to the next, rather than the actual series. In fact, as the magnitude of changes in
financial series is usually related to their levels, it is better to use first differences of the series after converting to logarithms. This results in a series that has the desirable statistical attribute of stationarity. That is, the mean and variance are constant over time and the autocovariance decreases as the lag increases. One of the features of financial series is that they are not, in general, stationary. In particular, the mean changes over time, the variance tends to increase over time, and first order serial correlation occurs with a value close to unity. In other words, the series tend to follow what is described by Nelson and Plosser (1982) as a difference stationary process. These authors distinguish between two different views concerning non-stationarity in economic time series: trend stationarity (i.e., stationary fluctuations around a deterministic trend) and difference stationarity (i.e., non-stationarity arising from the accumulation over time of stationary and invertible first differences). Within this framework difference stationary series, such as exchange rates can be made approximately stationary via the simple transformation of taking first differences (of logarithms) of the series. Taking first differences of a difference stationary series removes a linear trend and first order serial correlation of unity resulting in a differenced series with constant drift and zero first order serial correlation. Hence currency series are often described as representing a random walk with drift. It is the drift (trend in the actual series) that is of the most interest to the technical analyst.

It is important for the analyst to be aware of the difference stationary characteristic of currency series. Mechanical technical analysis approaches do not make the distinction between trend stationarity and difference stationarity clear. Some of the scepticism of mechanical technical analysis from statisticians arises from the fact that the mechanical techniques used do not appear to be related to standard statistical approaches and the difference stationary nature of financial series. Rather, mechanical technical analysis represents an ad-hoc application of chartist approaches with an attempt to remove the subjective elements. For example, the use of the standard deviation of the actual series in the construction of Bollinger Bands does not seem to take allowance of the fact that the standard deviation will not be constant over time and that over longer periods of time (e.g., over 50 days for daily data) there can be substantial changes in the mean and consequent changes in the standard deviation. The construction of bands, therefore, based on plus or minus two standard deviations from the mean, exacerbates statisticians, particularly where reference to the Normal distribution is made, as actual values of a financial price series are extremely unlikely to be Normally distributed.

The present authors have shown, however, that using first differences of the logarithms results in currency series that, at least over a relatively small number of data points (fewer than 50 days for daily data) have a stable mean and variance, and serial correlation close to zero (Pollock and Wilkie, 1996; Wilkie and Pollock, 1996; Pollock, Macaulay, Onkal-Atay and Wilkie-Thomson, 2002). Over longer periods of time, this transformed series has time varying mean and standard deviation. This form of distribution is consistent with the technical analysis philosophy that history repeats itself and price action reflects human psychology (Murphy, 1999). For instance, chart patterns, which have been identified and categorised over the last century, reflect certain representations that frequently appear on price series graphs, representations that illustrate the bullish or bearish psychology of the market. The task of the analyst is to assess the nature of the price series pattern and extrapolate this into the future because the future is assumed to be a repetition of the past.

Psychological factors influencing market participants have a key effect on the distribution of changes in currency series. Changes in exchange rates are the product of the diverse views of market participants - their optimism, pessimism and uncertainty. These views generate expectations that are aggregated to form the market sentiment that prevails in a particular period, in turn influencing the currency movements. The bullish and bearish sentiments in the market manifest themselves in a trend (non-zero mean drift in the original series). Primary trends may be viewed as lasting for more than one year and are perceived as reflecting the underlying sentiment of the market. As primary trends reflect the underlying psychology of the market they are more likely to continue than to reverse (Murphy, 1999). They are, therefore, associated with a relatively stable distribution over time. On the other hand, secondary trends are of much shorter term (i.e., one to three months) and basically mirror corrective actions of the financial players. For example, market participants may feel that short-term excessive bullish sentiment regarding a specific currency has been too strong in that the mean change has been excessively large; hence, they review their positions. This can result in a lower positive mean change or even a negative change in the short run reflecting a short-term reversal. Secondary trends can, therefore, cause the location parameter of the daily distribution to change in relatively short periods. This can explain why the mean of the distribution may be relatively stable over short periods of time but appears to change over longer horizons. In addition, the market will also be influenced by periods of stability and instability that are associated with collective uncertainty in the minds of the market participants associated with changing secondary trends. This causes variability in the dispersion parameter over relatively short periods of time.

One of the problems with technical analysis is that it does not easily fit into the statistical framework described above. The chartist’s use of visual representations of the actual series is, of course, very relevant. The graph of the actual currency series represents a pictorial presentation of potential returns that could accrue to holding the asset. For example, if over a specific time period, the exchange rate for the Euro with respect to the USD (Euro/USD) rises from 0.8 to 0.9, an initial amount of $1 million invested in euros at the beginning of the period would be valued at $1.125 million (i.e., 0.9/0.8 * 1 = 1.125) at the end of the period. The actual series, therefore, gives an insight into the underlying psychological factors such as fear, greed, and related uncertainties experienced by a breadth of market practitioners who will mainly concern themselves with what is happening to their returns from their positions. For the calculation of profit from a given position, however, it is necessary to consider the changes in the series over a period of time. The magnitude of these changes would, however, be related to the initial price. It is, therefore, appropriate to consider the percentage profit. In the above example, a profit of $0.125 million or 12.5% would have been made. As noted above, in the analysis of currency series, it is desirable to examine changes in the logarithms of the series. These show similar statistical characteristics to percentage changes in the series. Some aspects of mechanical technical analysis do use changes in the series, particularly oscillators and measures of momentum, but they do not really take into account the characteristics of the series.

There is a need, therefore, to extend mechanical technical analysis to take these issues into account. It is a fairly simple procedure to construct the first differences in the logarithms of a series and then, after setting an appropriate moving period (e.g., 9 days for daily data), obtain the mean as a measure of drift (trend in the original series) and standard deviation as a measure of volatility. A graph of these differences, means and standard deviations will clearly display characteristics in the series and, in addition, highlight any extreme (daily) movements in a specific moving period.
This fairly simple presentation can aid the analyst in making a prediction of future directional movements as well as the magnitude of movements. Results given in the form of changes in logarithms can easily be converted back to actual changes.

The next stage is the calculation of moving estimated probabilities (EPs) using these mean and standard deviation measures. At least for a limited number of data points (e.g., fewer than 30 days for daily data), there is evidence that these movements approximately follow a Normal distribution (Friedman and Vandersteel, 1982; Boothe and Glassman, 1987; Pollock and Wilkie, 1996; Wilkie and Pollock, 1996; Pollock et al, 2002 have illustrated this in relation to currency series). The moving estimated probabilities can be obtained from the moving means and standard deviations discussed above on the assumption that the first differences of logarithms are Normally distributed. This involves using the Student’s t distribution with degrees of freedom equal to the number of data points in the moving period less one (i.e., for a 9 day moving period the degrees of freedom would be 8). The Student’s t value is calculated by taking the square root of the number of data points in the moving period (i.e., square root of 9 = 3) and multiplying this by the ratio of the mean to the standard deviation. Then the cumulative probability is calculated to give the EP. A more formal explanation of the procedure is set out in Appendix 1 and the calculation of estimated probabilities is more fully explained in Pollock et al (2002).

The moving period EPs can also be presented on a graph and used to examine the characteristics of the financial price movements and to make buy and sell predictions. These probabilities can be used as a technical analysis indicator that reflects the strength of the direction of movement and momentum. EPs not only provide an extension to the traditional momentum indicators used in technical analysis but also have considerable advantages over them. These advantages are:

1. An upper bound of unity and a lower bound of zero. Technical analysis momentum measures do not necessarily have this property although the Relative Strength Index (RSI) and Stochastic oscillators have similar bounds in percentage terms.
2. Statistically significant movements can be directly identified. For instance EPs with values below 0.25 and above 0.975 can be viewed as being statistically significant, at the 5% level, from the zero change condition. While the RSI and Stochastics provide overbought and oversold bounds (e.g., above 70% and below 30%) they are essentially ad-hoc and do not have a statistically defined meaning.
3. A profit or loss over the horizon, on which the EPs are calculated, can be easily seen. That is, values below 0.5 indicate a loss and values above 0.5 indicate a profit. The traditional technical analysis momentum measures, with the exception of the simple Momentum and Price Rate of Changes oscillators, do not do this.
4. Volatility is directly incorporated into the EPs via the inclusion of the standard deviation of changes (in logarithms) in their construction. Traditional analysis momentum indicators do not directly take into account volatility.
5. The EPs can be used to make a direct ex-post comparison with probability predictions made at the beginning of the prediction period. Hence probability predictions can be evaluated on an interval scale and not just on the buy and sell decision basis.
6. EPs of various horizons can be presented on a multiple EP graph, e.g., a two EP graph displaying the 9-day EPs and the 25-day EPs. In using a graph of multiple EPs the shortest EP (e.g., 9-day) is the most important in detecting changes in momentum and indications of changes in trend and for timing purposes. The longer EP (e.g., 25-day) is used particularly to give a longer period view of the identify direction and strength of the trend. The use of multiple EPs has the advantage that the indicators can be used under various trend conditions. EPs can be used for daily, weekly and less frequent sampling intervals to determine actions in the presence of both secondary and primary trends moving in opposite directions and where there exists strong upward trends or flat trend conditions.

EPs are interpreted in a similar way to traditional technical analysis momentum indicators. They are, unlike the RSI, Stochastics and Moving Average Convergence / Divergence (MACD), equally applicable to trending and flat trend markets. In flat trend markets EPs will show activity as alternating values above 0.5 and below 0.5. In trending markets, however, EPs will tend to have values concentrated in the upper section of the chart (i.e., above 0.5) for upward trends and values concentrated in the lower section of the chart (below 0.5) for downwards trends. EPs also have the additional advantage that they can be used as an indicator of a change in the trend. This is shown up by large movements in the EPs. The interpretation of EPs is, like many technical analysis indicators, very dependent on the experience of the analyst using the technique. If a single EP is used it is generally better to use the EP chart in conjunction with a chart of the logarithms of the actual series. Traditional technical analysis can, therefore, be used in line with the EP approach. The multiple EP chart can, however, be used on its own as it contains much more market information than the single EP chart. A multiple EP chart can, however, be used in conjunction with other technical indicators.

**FORMING PROBABILITY PREDICTIONS**

In practice, when an analyst attempts to form probabilistic predictions for currency movements, it is critical for the supporting framework to effectively aid this process. Hence, it is essential that the adopted framework is

1. relatively easy to understand,
2. easy to use, and
3. flexible in allowing for quick predictions and updates.

The Normal distribution assumption with time varying means and standard deviations, in addition to being an appropriate specification for currency movements, provides such a framework. Specifically, for short periods of fewer than 50 days for daily data, the mean and standard deviations can be assumed approximately constant such that an analyst needs only to specify these two parameters in order to identify the subjective probability distribution. Furthermore, the framework can easily be extended to predictions for longer horizons. For instance, with weekly data on currency movements, Pollock and Wilkie (1996) illustrated that the Normal distribution is appropriate for predictions of up to a three-month horizon. With monthly data Wilkie and Pollock (1996) illustrated that it is appropriate for horizons of up to one year.

The assumption of Normally distributed changes in the logarithms of financial price series over short periods of time eludes the problem of identifying an alternative probability distribution. The three-stage procedure of forming subjective probabilities suggested by Cottrell, Girard and Rouset (1998) (i.e., the forecast of the mean level, the standard deviation (scatter) and a normalised profile (shape)) is hence reduced to a two-stage procedure. That is, the formation of a subjective probability only requires subjective estimates of two parameters, the mean and the standard deviation of the distribution. From these assessments, a subjective prediction interval for the mean change may be obtained.
There are, however, a number of requirements for an analyst to make effective judgemental probability predictions (or point estimates, or predictions of directional change). In particular, the analyst has to:

1. possess "structural knowledge" (Kurz, 1994), including knowledge of the process generating the series (e.g., difference stationary) and the form of the probability distribution of change (e.g., Normal);
2. be able to construct subjective estimates of the parameters of the distribution (i.e., estimates of the mean and standard deviation);
3. be able to use these estimated parameters in the formation of probability predictions;
4. receive feedback on previous performance to enable comparisons with probability and parameter estimates obtained from the realised values of the series at the end of the predictive horizon.

To form probability predictions the analyst first needs to undertake some analysis of the series. This can be carried out using traditional technical analysis that could be supplemented using, for instance, the graphical presentations of the mean, standard deviations and probabilities discussed above. The latter would provide a benchmark from which the judgmentally assessed means, standard deviations and probabilities could be formed. In addition, further statistical techniques could be used to support the analyst's efforts in constructing the judgemental predictions.

The analyst's next step, for a given predictive horizon, is to specify the subjective parameters (mean and standard deviation of the daily changes) and the probability of a price change over the predictive horizon. The stages involved in this process are:

1. make a subjective prediction for the daily mean change;
2. make a subjective prediction for the standard deviation of daily changes;
3. use these predictions to obtain a subjective Normalised Z value, which is equal to the square root of the number of data points in the predictive horizon multiplied by the ratio of the predicted mean to the standard deviation;
4. obtain the implied subjective probability via the cumulative distribution function of the Standard Normal; and
5. make any revisions to the subjective mean and standard deviation in the light of the derived subjective probability.

This iterative process can be continued until the analyst is content with the subjective mean, standard deviation and probability.

A more formal explanation of this procedure is set out in Appendix 2.

Using the above procedure, an analyst can make probability predictions based on the Normal distribution. If, within this framework, an analyst gives a high probability for a positive move, as compared with a probability close to 0.5, it implies that he or she feels that the movement in the series, scaled by the standard deviation, will be a relatively large positive one. If the analyst gives a low probability for a positive move it implies that the analyst feels the movement in the series will be a relatively large negative one. On the other hand, if the probability is close to 0.5 it suggests the analyst feels that there will be little or no change in the series. In other words, the forecaster's assessment of the probability of a movement in a particular direction can be viewed as a transformation of his or her assessment of the subjective mean and standard deviation, via a cumulative distribution function, to the probability domain.

**EVALUATION OF PROBABILITY PREDICTIONS**

It is also important for performance appraisal purposes that the forecasting performance is effectively evaluated at the end of the predictive horizon so that feedback becomes available on the accuracy of predictions. Specifically, at the end of the predictive horizon, a comparison of the subjective mean, standard deviation and corresponding probability can be made with the mean, standard deviation and associated probability estimated from the series. This can be extended to calculating values for a number of consecutive, non-overlapping periods (that form the whole period) to evaluate the accuracy of the predictions. These results can then be used to identify strengths and weaknesses in the predictions, highlighting areas for improvements in predictive strategies and pinpointing additional information needs. The framework can easily be extended to compare recommendations given by an analyst grouped into a number of categories. For example, an analyst could set bands for the GBP/USD exchange rate associated with probability statements as follows:

- 0 to 0.2 — buy USD assets and sell GBP assets;
- 0.21 to 0.4 — hold existing USD assets but reduce holdings of GBP assets;
- 0.41 to 0.59 — attempt to balance holdings of USD and GBP assets;
- 0.6 to 0.79 — hold GBP assets and reduce holdings of USD assets, and;
- 0.8 to 1 — buy GBP assets and sell USD assets.

The estimated probabilities and analyst's recommendations can then be presented and grouped, into a simple cross tabulation to provide a straightforward method of examining the analyst's predictive performance.

**CONCLUSION**

It is illustrated that moving period EPs can be used to examine financial price movements and generate buy or sell signals in a profitability context. These EPs measure the strength and momentum of market movements in an integrated form that gives considerable advantages over traditional analysis momentum indicators. Furthermore, they are derived from a statistically formulated framework based on the Normal distribution and the behaviour of currency. Accordingly, these EPs do not suffer from the problem often associated with mechanical technical analysis tools that may portray ad-hoc measures of chartist concepts. The framework also has considerable practical application to the evaluation of predictive performance when probability recommendations are made accompanying the prediction of a directional move.

The suggested framework set out above may carry considerable advantages in the practical formation of probability recommendations accompanying directional predictions of currency movements. Firstly, the process involves the setting of probabilities where the forecaster has a clear probability distribution defined (i.e., Normal). Secondly, the formation of probabilities is integrated into a process that incorporates predictions inherently framed by views as to future optimism and pessimism in the market (mean) and volatility (standard deviation). That is, the construction of predictive probabilities is directly related to forecasts of exchange rate changes and the uncertainties that prevail. Thirdly, the framework allows the performance of subjective predictions of all three components (mean, standard deviation and probability) to be evaluated using estimates at the end of pertinent predictive horizons, hence utilising the information content of forecast errors. It has been suggested that the uncertainty enveloping the point and directional forecasts may better be expressed in formats that explicitly recognise and communicate this uncertainty, e.g., via prediction intervals (Chatfield, 1993) or probability forecasts (Murphy and Winkler, 1984)). The procedure set out above provides a promising framework that clearly acknowledges the financial dynamics resulting from these uncertainties.
from prevailing uncertainties in such markets.

The framework described in this paper has considerable implications for technical analysts. It may be argued that subjective probability predictions need to be made in an integrated framework that allows for explicit performance feedback (Önkal-Atay, 1998). This framework should be related to the statistical distribution of the series being predicted, with subjective predictions of the parameters of the distribution elicited in addition to the subjective probabilities. Performance analysis can then be directly applied to the subjective predictions using realised estimates to provide valuable feedback to further enhance performance. In practice, it has been illustrated that the Normal distribution tailors an appropriate model of changes in the logarithms of currency series for forming subjective probabilities on tactical market movements. The suggested framework further provides a foundation for the development of consistent subjective probability predictions for currency movements while enabling promising extensions of current work on probability judgement accuracy such as combining probability currency predictions.

**APPENDIX 1**

**Calculating Estimated Probabilities**

The procedure for obtaining the estimated probabilities is detailed below.

Specifically the framework involves the following stages.

1. For day \( i \), \( i=1,2,...,n \), for a moving period \( j \) of length \( n \), let \( \Delta x_{ij} = x_{ij} - x_{i-1j} \) denote the change in the logarithm of the exchange rate. The mean of the daily changes, \( m_j \), is then obtained.
2. The standard deviation of the daily changes, \( s_j \) is calculated.
3. The quantity, \( t_j = \sqrt{n} \left( \frac{m_j}{s_j} \right) \) is obtained where \( s_j \) is the length of the predictive period and \( Z_{\alpha/2} \) is the upper critical value form the Standard Normal distribution. (e.g., for a 95% confidence interval \( Z_{\alpha/2} \) is 1.96).
4. Use the \( m_j \) and \( s_j \) estimates to obtain a subjective Normalised Z value, where \( Z = \sqrt{n} \left( \frac{m_j}{s_j} \right) \). The estimated probability is then \( Z \), corresponding to a rise in the exchange rate.

To illustrate this framework and calculation of estimated probabilities, suppose that the GBP/USD exchange rate moves from an initial value of 1 GBP=1.60 USD in Day 0 to a value of 1 GBP=1.65 USD in Day 5 as given below:

<table>
<thead>
<tr>
<th>Day No.</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ex. Rate (X)</td>
<td>1.60</td>
<td>1.61</td>
<td>1.59</td>
<td>1.62</td>
<td>1.64</td>
<td>1.65</td>
</tr>
<tr>
<td>Log. Ex. Rate (x)</td>
<td>0.20412</td>
<td>0.20683</td>
<td>0.20140</td>
<td>0.20952</td>
<td>0.21484</td>
<td>0.21748</td>
</tr>
<tr>
<td>Change Log. Ex. Rate (( \Delta x ))</td>
<td>0.00271</td>
<td>0.00543</td>
<td>0.00812</td>
<td>0.00533</td>
<td>0.00264</td>
<td></td>
</tr>
</tbody>
</table>

The first row gives the day number and the second row gives the exchange rate. The third row gives the logarithms to base 10 of the exchange rate. The fourth row gives the first differences in the logarithms of the rate. It is this last row that provides the basic input data to derive the estimated probabilities.

The four stages used to derive the estimated probabilities for this series can be applied as follows:

1. Calculate the mean, \( m = 0.00267 \).
2. Calculate the standard deviation, \( s = 0.00506 \).
3. Obtain the \( t \) value, \( t = \sqrt{5} \left( \frac{0.00267}{0.00506} \right) = 1.182 \).
4. Obtain the cumulative probability, \( \Phi(1.182) = \Phi(t < 1.182) = 0.849 \), using Student’s \( t \)-distribution with \( n-1 = 4 \) degrees of freedom. The estimated probability is then 0.849, corresponding to a rise in the exchange rate.
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BIographies

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