Forecasting FX Rates

Fundamental and Technical Models

Forecasting Exchange Rates

Model Needed
A forecast needs a model, which specifies a function for \( S_t \):
\[
S_t = f(X_t)
\]

- The model can be based on
  - Economic Theory (say, PPP: \( X_t = (I_{d,t} - I_{f,t}) \Rightarrow f(X_t) = I_{d,t} - I_{f,t} \))
  - Technical Analysis (say, past trends)
  - Statistics
  - Experience of forecaster
  - Combination of all of the above
Forecasting: Basics

• A forecast is an expectation –i.e., what we expect on average:
  \[ E_t[S_{t+T}] \Rightarrow \text{Expectation of } S_{t+T} \text{ taken at time } t. \]

• It is easier to predict changes. We will concentrate on \( E_t[s_{t+1}] \).
  \[ \text{Note: From } E_t[s_{t+1}], \text{ we get } E_t[S_{t+1}] \Rightarrow E_t[S_{t+1}] = S_t \times (1 + E_t[s_{t+1}]) \]

• Based on a model for \( S_t \), we are able to generate \( E_t[S_{t+1}] \):
  \[ S_t = f(X_t) \Rightarrow E_t[S_{t+1}] = E_t[f(X_{t+1})] \]

Assumptions needed for \( X_{t+T} \)

Today, we do not know \( X_{t+T} \). We will make assumptions to get \( X_{t+T} \).

Example: \( X_{t+T} = h(Z_t), \quad Z_t: \text{data available today.} \)
  \[ \Rightarrow \text{We'll use } Z_t \text{ to forecast the future } S_{t+T}: E_t[S_{t+1}] = g(Z_t) \]

Example: What is \( g(Z_t) \)?

Suppose we are interest in forecasting USD/GBP changes using PPP:

1. Model for \( S_t \)
  \[ E_t[s_{t+1}] = s_{t+1}^F = \frac{s_{t+1}^F}{S_t} - 1 \approx I_{d,t+1} - I_{f,t+1} \]

Now, once we have \( s_{t+1}^F \), we can forecast the level \( S_{t+1} \):
  \[ E_t[S_{t+1}] = S_t \times [1 + s_{t+1}^F] = S_t \times [1 + (I_{US,t+1} - I_{UK,t+1})] \]

2. Assumption for \( I_{t+1} \Rightarrow I_{t+1} = h(Z_t) \)
   - \( I_{US,t+1} = \alpha_0^{US} + \alpha_1^{US} I_{US,t} \)
   - \( I_{UK,t+1} = \alpha_0^{UK} + \alpha_1^{UK} I_{UK,t} \)

3. \( E_t[S_{t+1}] = g(Z_t) \)
   - \( E_t[S_{t+1}] = g(I_{US,t}, I_{UK,t}) \)
     \[ = S_t \times [1 + \alpha_0^{US} + \alpha_1^{US} I_{US,t} - \alpha_0^{UK} - \alpha_1^{UK} I_{UK,t}] \]
There are two forecasts: *in-sample* and *out-of-sample*.

- *In-sample*: It uses sample info to forecast sample values. Not really forecasting, it can be used to evaluate the fit of a model.
- *Out-of-sample*: It uses the sample info to forecast values outside the sample. In time series, it forecasts into the future.

**Two Pure Approaches to Forecasting**

Based on how we select the “driving” variables $X_t$ we have different forecasting approaches:

- Fundamental (based on data considered fundamental).
- Technical analysis or TA (based on data that incorporates only past prices: $P_{t-1}, P_{t-2}, P_{t-3}, \ldots$).

**Fundamental Approach**

**Economic Model**

We generate $E_t[S_{t+T}] = E_t[f(X_{t+T})] = g(X_t)$, where $X_t$ is a dataset regarded as *fundamental* economic variables:

- GNP growth rate,
- Current Account,
- Interest rates,
- Inflation rates, etc.

*Fundamental variables*: Taken from *economic models* (PPP, IFE, etc.)

$\Rightarrow$ the economic model says how the fundamental data relates to $S_t$. That is, the economic model specifies $f(X_t)$ – for PPP, $f(X_t) = I_{d,t} - I_{f,t}$
- The economic model usually incorporates:
  - Statistical characteristics of the data (seasonality, etc.)
  - Experience of the forecaster (what info to use, lags, etc.)

  \[ \Rightarrow \text{Mixture of art and science.} \]

**Fundamental Forecasting: Steps**

1. Selection of Model (say, PPP model) used to generate the forecasts.
2. Collection of \( S_t, X_t \) (for PPP: exchange rates and CPI data needed.)
3. Estimation of model, if needed (regression, other methods)
4. Generation of forecasts based on estimated model. Assumptions about \( X_{t+T} \) may be needed.
5. Evaluation. Forecasts are evaluated. If forecasts are very bad, model must be changed. Popular metrics to evaluate forecasts:

  \[ \Rightarrow \text{MSE (Mean Square Error)} = \frac{\sum_{j=1}^{Q} (S_{t+j} - \hat{S}_{t+j})^2}{Q} \]

  \[ \Rightarrow \text{MAE (Mean Absolute Error)} = \frac{\sum_{j=1}^{Q} |S_{t+j} - \hat{S}_{t+j}|}{Q} \]
Fundamental Forecasting: Process for Building Forecasting Model

1) Select a (long) part of the sample to select a model and estimate the parameters of the selected model. (You get in-sample forecasts.)
2) Keep a (short) part of the sample to check the model’s forecasting skills. This is the validation step. You can calculate true MSE or MAE.
3) Forecast out-of-sample.
Out-of-Sample Forecasting: Estimation and Validation Period

**Example: In-sample PPP forecasting of USD/GBP**

PPP equation for USD/GBP changes:

\[
E_t(s_{t+1}) = s^F_{t+1} \approx I_{US,t+1} - I_{UK,t+1} \Rightarrow E_t[s_{t+1}] = S_{t+1} = S_t \cdot [1 + s^F_{t+1}]
\]


\[P_{d=US}: \text{US-CPI: } 149.4, 150.2, 151.3\]
\[P_{f=UK}: \text{UK-CPI: } 167.4, 170.0, 170.4\]

\[S_{1996:1} = 1.5262 \text{ USD/GBP.}\]
\[S_{1996:2} = 1.5529 \text{ USD/GBP.}\]

1. **Forecast** \(S^F_{1996:2}\)

\[I_{US,1996:2} = (USCPI_{1996:2}/USCPI_{1996:1}) - 1 = (150.2/149.4) - 1 = .00535.\]
\[I_{UK,1996:2} = (UKCPI_{1996:2}/UKCPI_{1996:1}) - 1 = (170.0/167.4) - 1 = .01553\]
\[s^F_{1996:2} = I_{US,1996:2} - I_{UK,1996:2} = .00535 - .01553 = -.01018.\]
\[S^F_{1996:2} = S_{1996:1} \cdot [1 + s^F_{1996:2}] = 1.5262 \text{ USD/GBP} \cdot [1 + (-.01018)] = 1.5107 \text{ USD/GBP.}\]
• **Example (continuation):** *In-sample* PPP forecasting

\[ S_{1996:2}^F = 1.5107 \text{ USD/GBP} \]

2. **Forecast evaluation (Forecast error: \( S_{1996:2}^F - S_{1996:2} \))**

\[ \epsilon_{1996:2}^F = S_{1996:2}^F - S_{1996:2} = 1.5107 - 1.5529 = -0.0422. \]

For the whole sample:

<table>
<thead>
<tr>
<th>Date</th>
<th>CPI U.S.</th>
<th>CPI UK.</th>
<th>In-Sample Forecast ( (S_{out}^F) )</th>
<th>Actual ( S_t )</th>
<th>Forecast Error ( \epsilon_{1996:2}^F )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996:1</td>
<td>149.4</td>
<td>167.4</td>
<td>1.5262</td>
<td>1.5262</td>
<td>-</td>
</tr>
<tr>
<td>1996:2</td>
<td>150.2</td>
<td>170.0</td>
<td>1.5107</td>
<td>1.5529</td>
<td>-0.0422</td>
</tr>
<tr>
<td>1996:3</td>
<td>151.3</td>
<td>170.4</td>
<td>1.5182</td>
<td>1.563</td>
<td>-0.047</td>
</tr>
<tr>
<td>1996:4</td>
<td>152.6</td>
<td>171.5</td>
<td>1.5214</td>
<td>1.7123</td>
<td>-0.1909</td>
</tr>
<tr>
<td>1997:1</td>
<td>153.2</td>
<td>173.3</td>
<td>1.5114</td>
<td>1.6448</td>
<td>-0.1334</td>
</tr>
<tr>
<td>1997:2</td>
<td>154.1</td>
<td>176.0</td>
<td>1.4968</td>
<td>1.665</td>
<td>-0.1682</td>
</tr>
<tr>
<td>1997:3</td>
<td>155.6</td>
<td>179.0</td>
<td>1.4858</td>
<td>1.6147</td>
<td>-0.1259</td>
</tr>
</tbody>
</table>

**MSE:** \[ \frac{(-0.0422)^2 + (-0.0471)^2 + ... + (-0.1259)^2}{6} = 0.017063278 \]

Note: Not a true forecasting model. At time \( t \), \( I_{t+1} \) is unknown. We need \( E_t[I_{t+1}] \).

**Example:** *Out-of-sample* Forecast: \( E_t[S_{t+1}] \)

- Simple forecasting model: Naive forecast \( (E_t[I_{t+1}] = I_t) \)

\[ E_t[S_{t+1}] = s_{t+1}^F = (E_t[S_{t+1}]/S_t) - 1 \approx I_{dt} - I_{ft}. \]

Using the above information we can predict \( S_{1996:3} \):

1. **Forecast \( S_{1996:3}^F \)**

\[ s_{1996:3}^F = I_{US,1996:2} - I_{UK,1996:2} = .00535 - .01553 = -0.01018. \]

\[ S_{1996:3}^F = S_{1996:2} \cdot [1 + s_{1996:3}^F] = 1.5529 \cdot [1 + (-0.01018)] = 1.53709 \]

2. **Forecast evaluation**

\[ \epsilon_{1996:3}^F = S_{1996:3}^F - S_{1996:3} = 1.53709 - 1.5653 = -0.028210. \]
More sophisticated out-of-sample forecasts can be achieved by estimating regression models, survey data on expectations of inflation, etc. For example, consider the following regression model:

\[ I_{US,t} = \alpha_0^{US} + \alpha_1^{US} I_{US,t-1} + \varepsilon_{US,t} \]

\[ I_{UK,t} = \alpha_0^{UK} + \alpha_1^{UK} I_{UK,t-1} + \varepsilon_{UK,t} \]

Suppose we estimate both equations. The estimated coefficients (\( a \)'s) are:

\[ a_0^{US} = .0036, \quad a_1^{US} = .64, \quad a_0^{UK} = .0069, \quad \text{and} \quad a_1^{UK} = .43. \]

Therefore,

\[ I_{US,1996:3}^F = .0036 + .64 \times (0.00535) = .007024 \]
\[ I_{UK,1996:3}^F = .0069 + .43 \times (0.01553) = .013578. \]

\[ S_{1996:3}^F = I_{US,1996:3}^F - I_{UK,1996:3}^F = .007024 - .013578 = -.00655. \]
\[ S_{1996:3}^F = 1.5529 \text{ USD/GBP} \times [1 + (-.00655)] = 1.5427 \text{ USD/GBP}. \]
\[ \varepsilon_{1996:3} = S_{1996:3}^F - S_{1996:3} = 1.5427 - 1.5653 = -0.0226. \]

**Example**: Exchange Rate Forecasts

US Excel Regression Results for US Inflation Forecasts (\( I_{US,t+1}^{US} \)):

<table>
<thead>
<tr>
<th>Regression Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
</tr>
<tr>
<td>R Square</td>
</tr>
<tr>
<td>Adjusted R Square</td>
</tr>
<tr>
<td>Standard Error</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

**ANOVA**

<table>
<thead>
<tr>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>Significance F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>0.003748</td>
<td>0.003748</td>
<td>80.80752</td>
</tr>
<tr>
<td>Residual</td>
<td>123</td>
<td>0.000705</td>
<td>0.000705</td>
<td>4.64E-05</td>
</tr>
<tr>
<td>Total</td>
<td>124</td>
<td>0.004454</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Coefficients**

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.00366</td>
<td>0.000923</td>
<td>3.965867</td>
</tr>
<tr>
<td>X Variable 1</td>
<td>0.640707</td>
<td>0.071274</td>
<td>8.9893</td>
</tr>
</tbody>
</table>

How much variability of \( Y_t \) is explained by \( X_t \)

\[ t_{stat} \text{ tests } H_0: \ a_i=0 \]
\[ t_{stat} = \frac{a_i}{SE(a_i)} = \frac{0.640707}{0.071274} = 8.9893 \]
Example (continuation): Inflation Forecasts - UK Regression Results:

SUMMARY OUTPUT

Regression Statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.425407</td>
</tr>
<tr>
<td>R Square</td>
<td>0.180971</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.174312</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.011305</td>
</tr>
<tr>
<td>Observations</td>
<td>125</td>
</tr>
</tbody>
</table>

I\(_{UK,t-1}\) explains 18.10% of the variability of I\(_{UK,t}\)

\(t\)-stat is significant at the 5% level (|t|>1.96)

=> Lagged Inflation explains current Inflation

ANOV A

<table>
<thead>
<tr>
<th></th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>Significance F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>0.003473</td>
<td>0.003473</td>
<td>27.17784</td>
<td>7.6E-07</td>
</tr>
<tr>
<td>Residual</td>
<td>123</td>
<td>0.015719</td>
<td>0.000128</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>124</td>
<td>0.019192</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Coefficients

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.006918</td>
<td>4.932637</td>
<td>2.57E-06</td>
</tr>
<tr>
<td>X Variable 1</td>
<td>0.428132</td>
<td>5.213237</td>
<td>7.6E-07</td>
</tr>
</tbody>
</table>

Example: Out-of-sample Forecasting FX with an Ad-hoc Model

Forecast monthly MYR/USD changes with the following model:

\[ s_{MYR/USD,t} = \alpha_0 + \alpha_1 (I_{MYR} - I_{USD})_t + \alpha_2 (y_{MYR} - y_{USD})_t + \varepsilon_t \]

Excel Regression Results:

SUMMARY OUTPUT

Regression Statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.092703</td>
</tr>
<tr>
<td>R Square</td>
<td>0.018594</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>-0.0087</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.051729</td>
</tr>
<tr>
<td>Observations</td>
<td>112</td>
</tr>
</tbody>
</table>

X\(_t\) explains 1.86% of the variability of \(s_t\)

\(t\)-stat tests \(H_0: \alpha_i = 0\)

\[ t_{\alpha_i} = \frac{\alpha_i}{SE(\alpha_i)} = \frac{0.215927}{0.105824} = 2.040435 \]

ANOV A

<table>
<thead>
<tr>
<th></th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>Significance F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>2</td>
<td>0.002528</td>
<td>0.001264</td>
<td>0.47242</td>
<td>0.624762</td>
</tr>
<tr>
<td>Residual</td>
<td>109</td>
<td>0.291666</td>
<td>0.002676</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>111</td>
<td>0.294195</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Coefficients

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.006934</td>
<td>1.339903</td>
<td>0.180277</td>
</tr>
<tr>
<td>X Variable 1 (I_{MYR} - I_{USD})</td>
<td>0.215927</td>
<td>2.040435</td>
<td>0.041307</td>
</tr>
<tr>
<td>X Variable 2 (y_{MYR} - y_{USD})</td>
<td>0.091592</td>
<td>1.772428</td>
<td>0.076326</td>
</tr>
</tbody>
</table>
Example (continuation): Out-of-sample Forecasting w/Ad-hoc Model

\[ s_{MYR/USD,t} = \alpha_0 + \alpha_1 (I_{MYR} - I_{USD})_t + \alpha_2 (y_{MYR} - y_{USD})_t + \epsilon_t \]

0. Model Evaluation

Estimated coefficient: \( a_0 = .0069 \), \( a_1 = .2159 \), and \( a_2 = .0915 \).

- \( t \)-stats: \( t_{a_1} = 2.040435 > 1.96 \) (reject \( H_0 \)), \( t_{a_2} = 1.772428 < 1.96 \) (can’t reject \( H_0 \))

Do the signs make sense?

- \( a_1 = .2159 > 0 \) => PPP
- \( a_2 = .0915 > 0 \) => Trade Balance

1. Forecast \( S_{t+1}^F \)

\[ E[s_{MYR/USD,t}] = .0069 + .2159 (I_{MYR} - I_{USD})_t + .0915 (y_{MYR} - y_{USD})_t \]

Forecasts for next month (\( t+1 \)): \( E_t[\text{INF}_{t+1}] = 3\% \) & \( E_t[\text{INC}_{t+1}] = 2\% \).

\[ E_t[s_{MYR/USD,t+1}] = .0069 + .2159 * (.03) + .09157 * (.02) = .0152. \]

The MYR is predicted to depreciate 1.52% against the USD next month.

Example (continuation): Out-of-sample Forecasting w/Ad-hoc Model

1. Forecast \( S_{t+1}^F \) (continuation)

\[ E_t[s_{MYR/USD,t+1}] = .0152. \]

Suppose \( S_t = 3.1021 \text{ MYR/USD} \)

\[ S_{t+1}^F = 3.1021 \text{ MYR/USD} * (1 + .0152) = 3.1493 \text{ MYR/USD}. \]

2. Forecast evaluation

Suppose \( S_{t+1} = 3.0670 \text{ MYR/USD} \).

\[ \epsilon_{t+1} = S_{t+1}^F - S_{t+1} = 3.1493 - 3.0670 = 0.0823. \]
**Practical Issues in Fundamental Forecasting**

Issues:

- Are we using the "right model?"
- Estimation of the model.
- Some explanatory variables ($Z_{t+T}$) are contemporaneous.
  
  $\Rightarrow$ We also need a model to forecast the $Z_{t+T}$ variables.

**Does Forecasting Work?**

RW models beat structural (and other) models: Lower MSE, MAE.

Richard Levich compared forecasting services to the free forward rate. He found that forecasting services may have some ability to predict direction (appreciation or depreciation).

For some investors, the direction is what really matters, not the error.

---

**Example:** Two forecasts: Forward Rate and Forecasting Service (FS)

$F_{t,1\text{-month}} = .7335$ USD/CAD  
$E_{FS,t}[S_{t+1\text{-month}}] = .7342$ USD/CAD.

(Sternin’s strategy: buy CAD forward if FS forecasts CAD appreciation.) Based on the FS forecast, Sternin buys CAD forward at $F_{t,1\text{-month}} = .7335$.

(A) Suppose that the CAD appreciates to $\text{.7390}$ USD/CAD. 
$\text{MAE}_{FS} = \text{.7390} - .7342 = .0052$ USD/CAD. 
Sternin makes a profit of $\text{.7390} - .7335 = .055$ USD/CAD.

(B) Suppose that the CAD depreciates to $\text{.7315}$ USD/CAD. 
$\text{MAE}_{FS} = |\text{.7315} - .7342| = .0027$ USD/CAD (smaller!) 
Sternin takes a loss of $\text{.7315} - .7335 = -.0020$ USD/CAD. ¶
Technical Analysis Approach

- Based on a small set of the available data: past price information.
Q: Why ignore fundamentals, say, (I_{t,t} – I_{t,t})?
EMH: FX market “discounts” public information regarding fundamentals
⇒ No need to research or forecast fundamentals.

- TA looks for the repetition of specific price patterns.
⇒ Discovering these patterns is an art, not a science.

- TA attempts to generate signals: trends and turning points.

- TA models range from very simple (say, looking at price charts) or very sophisticated, incorporating neural networks and genetic algorithms.

Technical Analysis Approach

- Popular models:
  - Moving Averages (MA)
  - Filters
  - Momentum indicators.
  - Bolling Bands (MA + SD, used to create “bands” for MA)
  - Relative Strength Index, RSI (it determines “over/under-sold”)
  - Fibonacci Retracements, “Fibs” (Fibonacci ratios determine potential retracements from a high)
**MA models**
The goal of MA models is to smooth the erratic daily swings of FX to signal major trends. We define $S_t^{MA}$ as SMA:

$$\text{SMA}_t = (S_t + S_{t-1} + S_{t-2} + ... + S_{t-(Q-1)})/Q$$

The *double MA system* uses two SMAs: Long-run MA, with $Q_L$ rates, and Short-run MA, with $Q_S$ rates, where $Q_L > Q_S$.

LRMA will always lag a SRMA (gives smaller weights to recent $S_t$).

**Example**: $S_t$ (USD/GBP) Double MA - $Q_L$=30 days (red); & $Q_S$=150 days (green).

Buy FC signal: When SRMA crosses LRMA from below.
Sell FC signal: When SRMA crosses LRMA from above.
(2) Filter models
The filter, X, is a percentage that helps a trader forecasts a trend.
Buy signal: when $S_t$ rises X% above its most recent trough.
Sell signal: when $S_t$ falls X% below the previous peak.

Idea:
When $S_t$ reaches a peak $\Rightarrow$ Sell FC
When $S_t$ reaches a trough $\Rightarrow$ Buy FC.

Key: Identifying the peak or trough. We use the filter to do it:

When $S_t$ moves X% above (below) its most recent peak (trough), we have a trading signal.

Example: X = 1%, $S_t$ (CHF/USD)

Peak = 1.486 CHF/USD ($X = CHF .01486$)
$\Rightarrow$ When $S_t$ crosses 1.47114 CHF/USD, Sell USD

Trough = 1.349 CHF/USD ($X = CHF .01349$)
$\Rightarrow$ When $S_t$ crosses 1.36249 CHF/USD, Buy USD
Example: $X = 1\%$, $S_t$ (CHF/USD)

Peak = 1.486 CHF/USD ($X = \text{CHF} .01486$)

$\Rightarrow$ When $S_t$ crosses 1.47114 CHF/USD, Sell USD

(3) **Momentum models**

They determine the strength of an asset by examining the change in velocity of asset prices’ movements.

We are looking at the second derivative (a change in the slope).

Buy signal: When $S_t$ climbs at increasing speed.

Sell signal: When $S_t$ decreases at increasing speed.
• **TA Newer Models:**
In MA and filter models, the TA practitioner needs to select a parameter (Q and X). This fact can make two TA practitioners using the same model, but different parameters, to generate different signals.

There are newer TA methods that rely on more sophisticated formulas to determine when to buy/sell, without the subjective selection of parameters.

Clements (2010, *Technical Analysis in FX Markets*) describes four of these methods: Relative strength indicator (RSI), Exponentially weighted moving average (EWMA), Moving average convergence divergence (MACD) and (iv) Rate of change (ROC).

• **TA Summary:**
TA models monitor the derivative (slope) of a time series graph. Signals are generated when the slope varies significantly.

• **Technical Approach: Evidence**
  - Against TA:
    • RW model: A good forecasting model.
    • Many economists have a negative view of TA:
      \[ \Rightarrow \text{TA runs against market efficiency.} \]
  - For TA:
    • Informal evidence: FX Mkt is full of TA newsletters & traders (30%).
    • Formal (academic) support:
      ◦ In general, in-sample results tend to be good (profitable). But, not out-of-sample.
      ◦ LeBaron (1999) speculates that the apparent success of TA in the FX market is influenced by the periods where there is CB intervention.
      ◦ Lo (2004): Markets are adaptive efficient: TA may work for a while.
      ◦ Ohlson (2004): Even in-sample, profitability has declined, with zero profits by the 1990s.