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 needs a **functional form** and a set of **driving variables**, X_t.

- Functional form, $f(X_t)$: In this class, **linear**
- Driving variables, X_t, can be based on
  - Economic Theory --say, PPP: $X_t = I_d - I_f \Rightarrow f(X_t) = I_{d,t} - I_{f,t}$
  - 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:

$E_t[S_{t+T}]$ ⇒ Expectation of S_{t+T} taken at time t ("*today*").

• Easier to predict changes ⇒ $E_t[e_{f,t+T}]$.

Note: From $E_t[e_{f,t+T}]$, we get $E_t[S_{t+T}]$ ⇒ $E_t[S_{t+T}] = S_t * (1+E_t[e_{f,t+T}])$

• Based on a model for S_t, we generate $E_t[S_{t+T}]$:

$S_t = f(X_t)$ ⇒ $E_t[S_{t+T}] = E_t[f(X_{t+T})]$

Assumptions needed for X_{t+T}

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

Example: $X_{t+T} = h(Z_t)$, –Z_t: Data available today.

⇒ We'll use Z_t to forecast the future S_{t+T}:

$E_t[S_{t+T}] = f(X_{t+T}) = f(h(Z_t)) = g(Z_t)$

Example: What is $g(Z_t)$?

Using PPP, we forecast USD/GBP changes one period ahead (T=1):

1. Model for S_t

$$E_t[e_{f,t+1}] = e^F_{f,t+1} = \frac{S^F_{t+1}}{S_t} - 1 \approx I_{d,t+1} - I_{f,t+1}$$

Now, once we have s^F_{t+1}, we can forecast the level S_{t+1}

$$E_t[S_{t+1}] = S_t * [1 + e^F_{f,t+1}] = S_t * [1 + (I_{US,t+1} - I_{UK,t+1})]$$

2. Assumption for I_{t+1} ⇒ $I_{t+1} = h(Z_t)$,

- $I_{US,t+1} = \alpha_0^{US} + \alpha_1^{US} I_{US,t}$
- $I_{UK,t+1} = \alpha_0^{UK} + \alpha_1^{UK} I_{UK,t}$

3. $E_t[S_{t+1}] = g(Z_t)$

- $E_t[S_{t+1}] = g(I_{US,t}, I_{UK,t})$

$$= S_t * [1 + \alpha_0^{US} + \alpha_1^{US} I_{US,t} - \alpha_0^{UK} - \alpha_1^{UK} I_{UK,t}]$$

• 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 the "driving" variables X_t, we have:

- Fundamental Approach, 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}, ...

Fundamental Approach

Economic Model

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

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

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

$\Rightarrow$ The model says how the fundamental data relates to S_t.

That is, the model specifies $f(X_t)$ –for PPP, $f(X_t) = I_{d,t} - I_{f,t}$

- The model, $f(X_t)$, usually incorporates:
  - **Statistical characteristics** of the data
  - **Experience** of the forecaster

    $\Rightarrow$ Mixture of **art** and s**cience**.

Fundamental Forecasting: Steps

(1) Selection of Model (say, PPP model).

(2) Get Data: S_t & X_t (for PPP: S_t & CPI data.)

(3) Estimation of model, if needed.

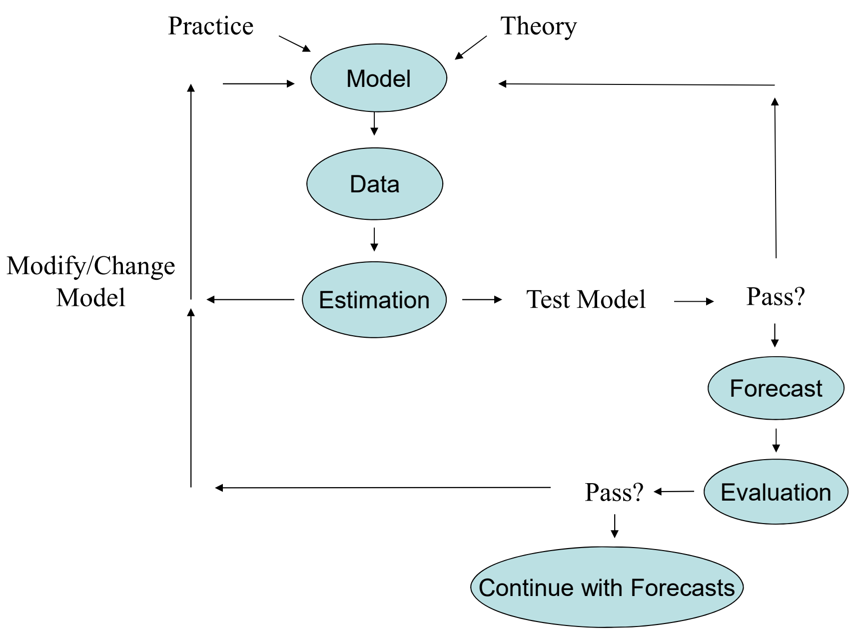
(4) Generation of forecasts. Assumptions about X_{t+T} may be needed.

(5) Evaluation of forecasts. If forecasts are bad, model must be changed. Popular evaluation metrics:

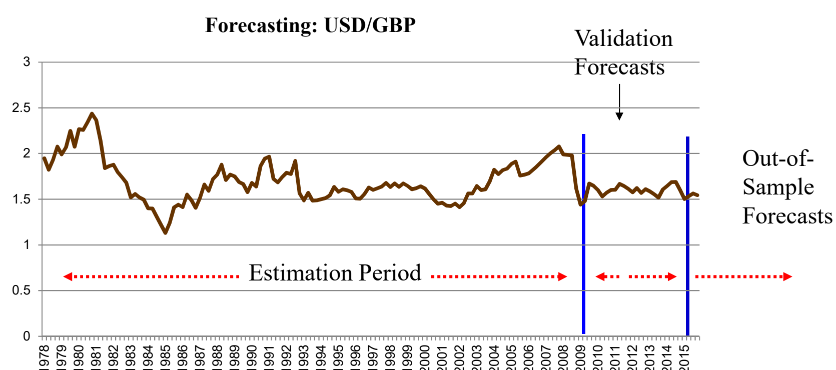
$$\Rightarrow \text{MSE (Mean Square Error)} = \frac{\sum_{J=1}^{Q}(S_{t+J} - S_{t+J}^{F})^2}{Q}$$

$$\Rightarrow \text{MAE (Mean Absolute Error)} = \frac{\sum_{J=1}^{Q} |S_{t+J} - S_{t+J}^{F}|}{Q}$$

Fundamental Forecasting: Process for Building Forecasting Model



Fundamental Forecasting: Usual Estimation Process



1) Select a (long) part of the sample to estimate the parameters of the selected model. This is the *estimation step*.

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) If happy with model from 1) & 2), forecast **out-of-sample**.

Fundamental Forecasting: Usual Estimation Process

Note: In the Machine Learning literature, the terminology used for the process to select a forecasting model is slightly different.

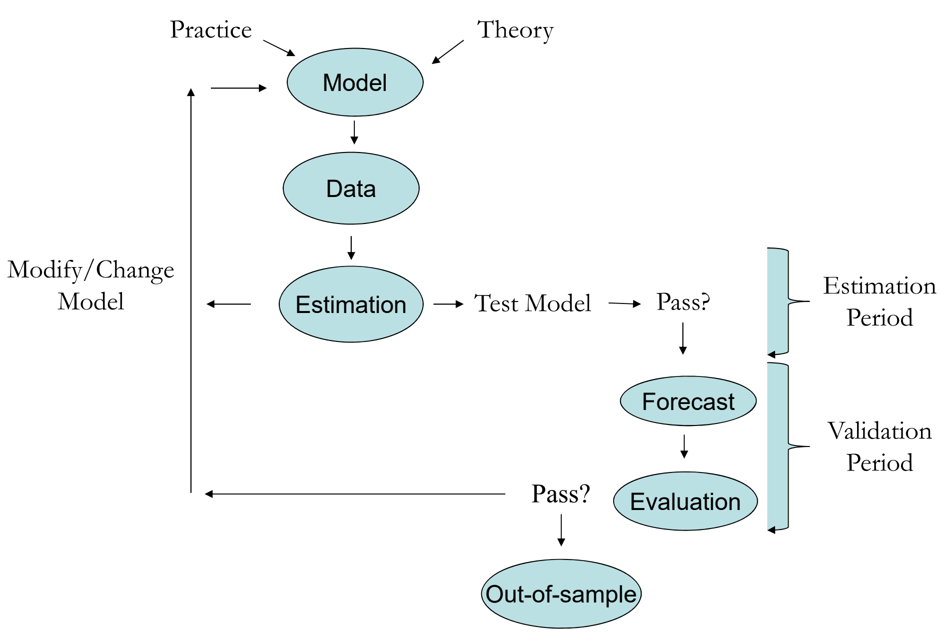
Step 1 is called *training step,* the data used (say, first T_1 observations) are called *training data/set*. In this step, we **estimate** the parameters of the model subject to assumptions, for example, PPP or Monetary Approach.

Step 2 has the same name, the *validation step*. This step is used to "*tune (hyper)parameters*." In our simple linear model, we **tune** by including more variables in the driving set X_t and re-estimating the model accordingly, using the "training data" alone. We choose the model with lower MSE or MAE

Remark: The idea of this step is to **simulate** out-of-sample accuracy. But, the "tuned" parameters selected in Step 2 are fed back to Step 1.

Step 3 tests the true out-of-sample forecast accuracy of the model selected by **Step 1** & **Step 2**. This last part of the sample is called "*testing sample*."

Out-of-Sample Forecasting: Estimation and Validation Period



Example 1: SEK/USD *Out-of-sample* Forecast: $E_t[S_{t+1}] = f(X_t)$

STEP 1 – Model

We start with a Model: Relative PPP:

$$e_{f,t} \approx I_{d,t} - I_{f,t}$$

We use it to forecast next period $e_{f,t}$: $e^F_{f,t+1}$

$$E_t[e_{f,t+T}] = e^F_{f,t+1} \approx I_{d,t+1} - I_{f,t+1}$$

• At time t, we do not know I_d & I_{UK} next period. We need a model to forecast $I_{d,t+1} - I_{f,t+1}$. For example, suppose we use a Random Walk Model for I_t (a Naive forecast). That is,

$$E_t[I_{t+1}] = I_t.$$

Then, for the SEK/USD exchange rate (SEK = Swedish Kronor)

$$E_t[e_{f,t+1}] = e^F_{f,t+1} = I_{SWED,t} - I_{US,t}$$

$$E_t[S_{t+1}] = S^F_{t+1} = S_t * (1 + I_{SWED,t} - I_{US,t})$$

Example 1 (continuation): Starting on 2023:2, we forecast 2023:3-2024:4:

STEP 2 – Data

Date	CPI_{SWED}	CPI_{US}	S_t	I_{SWED}	I_{US}	$e_{f,t}$	$I_{SW} - I_{US}$
1/1/2023	136.1820	300.356	10.3975				
2/1/2023	137.6847	301.509	**10.4492**	**0.0110**	**0.0038**	0.0050	**0.0072**
3/1/2023	138.4708	301.744	10.4763	0.0057	0.0008	0.0026	0.0049
4/1/2023	139.1143	303.032	10.3484	0.0046	0.0043	-0.0122	0.0004
5/1/2023	139.5526	303.365	10.4643	0.0032	0.0011	0.0112	0.0021
6/1/2023	141.0484	304.003	10.7691	0.0107	0.0021	0.0291	0.0086
7/1/2023	141.1110	304.628	10.5002	0.0004	0.0021	-0.0250	-0.0016
8/1/2023	141.2153	306.187	10.8291	0.0007	0.0051	0.0313	-0.0044
9/1/2023	141.9389	307.288	11.0848	0.0051	0.0036	0.0236	0.0015
10/1/2023	142.2937	307.531	11.0259	0.0025	0.0008	-0.0053	0.0017
11/1/2023	142.7389	308.024	10.6694	0.0031	0.0016	-0.0323	0.0015
12/1/2023	143.7790	308.742	10.2576	0.0073	0.0023	-0.0386	0.0050
1/1/2024	143.5703	309.685	10.3593	-0.0015	0.0031	0.0099	-0.0045
2/1/2024	143.9251	311.054	10.4266	0.0025	0.0044	0.0065	-0.0019
3/1/2024	144.0990	312.23	10.4113	0.0012	0.0038	-0.0015	-0.0026
4/1/2024	144.2981	313.207	10.8158	0.0014	0.0031	0.0389	-0.0017

1. Forecast $S^F_{2023:3}$

$e^F_{f,2023:3} = I_{SW,2023:2} - I_{US,2023:2} = .0110 - .00338 = 0.0072.$

$S^F_{2023:3} = S_{2023:2} * [1 + e^F_{f,2023:3}] = 10.4492 * [1 + 0.0072] = 10.5007$

Example 1 (continuation): Starting on 2023:2, we forecast 2023:3. We call this forecast *the one-step-ahead forecast.*

STEP 2 – Data

Date	CPI_{SWED}	CPI_{US}	S_t	I_{SWED}	I_{US}	$e_{f,t}$	$I_{SW} - I_{US}$
1/1/2023	136.1820	300.356	10.3975				
2/1/2023	137.6847	301.509	10.4492	0.0110	0.0038	0.0050	0.0072
3/1/2023	138.4708	301.744	10.4763	0.0057	0.0008	0.0026	0.0049

1. Forecast $S^F_{2023:3}$

$e^F_{f,2023:3} = I_{SW,2023:2} - I_{US,2023:2} = .0110 - .00338 = 0.0072.$

$S^F_{2023:3} = S_{2023:2} * [1 + e^F_{f,2023:3}] = 10.4492 * [1 + 0.0072] = 10.5007$

2. Forecast Evaluation

Next month, in 2023:3, we will compute the forecast error, $\varepsilon_{2023:3}$:

$\varepsilon_{2023:3} = S_{2023:3} - S^F_{2023:3} = 10.4763 - 10.5007 = -0.0244.$

To have a good yardstick, we compute the forecast error of the RW Model:

$\varepsilon^{RW}_{2023:3} = S_{2023:3} - S_{2023:3} = 10.4763 - 10.4492 = 0.0271$

Example 1 (continuation): Then, each month, we repeat this one-step-ahead forecasting process until the end of our sample, 2024:4

Date	S_t	$I_{SW} - I_{US}$	S^F_{t+1}	ε_{t+1}	$(\varepsilon_{t+1})^2$	$S^{F,RW}_{t+1}$	ε^{RW}_{t+1}	$(\varepsilon^{RW}_{t+1})^2$
1/1/2023	10.3975							
2/1/2023	10.4492	0.0072						
3/1/2023	10.4763	0.0049	10.5007	-0.0244	0.0006	10.4492	0.0271	0.0007
4/1/2023	10.3484	0.0004	10.4803	-0.1319	0.0174	10.4763	-0.1279	0.0164
5/1/2023	10.4643	0.0021	10.3696	0.0947	0.0090	10.3484	0.1159	0.0134
6/1/2023	10.7691	0.0086	10.5545	0.2146	0.0461	10.4643	0.3048	0.0929
7/1/2023	10.5002	-0.0016	10.7517	-0.2515	0.0633	10.7691	-0.2689	0.0723
8/1/2023	10.8291	-0.0044	10.4542	0.3749	0.1405	10.5002	0.3289	0.1082
9/1/2023	11.0848	0.0015	10.8456	0.2392	0.0572	10.8291	0.2557	0.0654
10/1/2023	11.0259	0.0017	11.1037	-0.0778	0.0061	11.0848	-0.0589	0.0035
11/1/2023	10.6694	0.0015	11.0427	-0.3733	0.1394	11.0259	-0.3565	0.1271
12/1/2023	10.2576	0.0050	10.7223	-0.4647	0.2159	10.6694	-0.4118	0.1696
1/1/2024	10.3593	-0.0045	10.2114	0.1479	0.0219	10.2576	0.1017	0.0103
2/1/2024	10.4266	-0.0019	10.3391	0.0875	0.0077	10.3593	0.0673	0.0045
3/1/2024	10.4113	-0.0026	10.3998	0.0115	0.0001	10.4266	-0.0153	0.0002
4/1/2024	10.8158	-0.0017	10.3931	0.4227	0.1787	10.4113	0.4045	0.1636
MSE					0.06455			0.06058

• In 2024:4, after generating all forecasts, and computing all one-step-ahead forecast errors, we compute the MSE $= \frac{\sum_{t=1}^{Q} \varepsilon^2_{t+T}}{Q}$ for both models.

More sophisticated forecasts using models for $I_{d,t}$ & $I_{f,t}$, survey data on expectations of I, etc.

Example 1A: AR(1) model for inflation,

$I_{SWED,t+1} = \alpha_0^{SWED} + \alpha_1^{SWED}\, I_{SWED,t} + \varepsilon_{SWED,t+1}$.

$I_{US,t+1} = \alpha_0^{US} + \alpha_1^{US}\, I_{US,t} + \varepsilon_{US,t+1}$.

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

$a_0^{US} = .0036$, $a_1^{US} = .64$, $a_0^{SWED} = .0069$, & $a_1^{SWED} = .43$.

$\Rightarrow I^F_{SWED,2023:3} = .0069 + .43 * (.0110) = .01163.$

$\Rightarrow I^F_{US,2023:3} = .0036 + .64 * (.00338) = .00576$

$e^F_{f,2023:3} = I^F_{SWED,2023:3} - I^F_{US,2023:3} = .01163 - .00576 = .00587$.

$S^F_{2023:3} = 10.4492$ SEK/USD * [1 + .00587] = 10.5105 USD/GBP.

$\varepsilon_{2023:3} = S_{2023:3} - S^F_{2023:3} = 10.4763 - 10.5105 = -0.0342$.

Example 1A (continuation): Exchange Rate Forecasts

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

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.629674
R Square	0.396489
Adjusted R Square	0.391583
Standard Error	0.006811
Observations	125

How much variability of Y_t is explained by X_t

t-stat tests H_o: $a_i=0$

$t_{a1}=a_1/SE(a_1)= 0.640707/0.071274=8.9893$

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.003748	0.003748	80.80752	3.66E-15
Residual	123	0.005705	4.64E-05		
Total	124	0.009454			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.00366	0.000923	3.965867	0.000123
X Variable 1	0.640707	0.071274	8.9893	3.66E-15

Example 1A (continuation): $I_{SWED,t}$ - Swedish Regression Results:

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.425407
R Square	**0.180971**
Adjusted R Square	0.174312
Standard Error	0.011305
Observations	125

$I_{SWED,t-1}$ explains **18.10%** of the variability of $I_{SWED,t}$

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

=> Lagged Inflation explains current Inflation

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.003473	0.003473	27.17784	7.6E-07
Residual	123	0.015719	0.000128		
Total	124	0.019192			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	**0.006918**	**0.001403**	**4.932637**	2.57E-06
X Variable 1	**0.428132**	**0.082124**	**5.213237**	7.6E-07

Example 2: *Out-of-sample* Forecasting FX with an Ad-hoc Model

Forecast monthly MYR/USD changes with the following model:

$$e_{f,t}\ (\text{MYR/USD}) = a_0 + a_1\,(I_{MY,t} - I_{US,t}) + a_2\,(y_{MY,t} - y_{US,t}) + \varepsilon_t$$

Excel Regression Results:

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.092703
R Square	0.018594
Adjusted R Square	-0.0087
Standard Error	0.051729
Observations	112

X_t explains 1.86% of the variability of s_t

t-stat tests H_o: $\alpha_i = 0$

$t_{\alpha 1} = a_1/\text{SE}(a_1) =$ **0.215927**/**0.105824** = **2.040435**

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	0.002528	0.001264	0.47242	0.624762
Residual	109	0.291666	0.002676		
Total	111	0.294195			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	**0.006934**	**0.005175**	**1.339903**	0.180277
X Variable 1 $(I_{MYR} - I_{USD})_t$	**0.215927**	**0.105824**	**2.040435**	0.041307
X Variable 2 $(y_{MYR} - y_{USD})_t$	**0.091592**	**0.051676**	**1.772428**	0.076326

Example 2 (continuation): Out-of-sample Forecasting w/Ad-hoc Model

$e_{f,t}$ (MYR/USD) = $a_0 + a_1 (I_{MY,t} - I_{US,t}) + a_2 (y_{MY,t} - y_{US,t}) + \varepsilon_t$

0. Model Evaluation

Estimated coefficient: a_0 = **.0069**, a_1 = **.2159**, and a_2 = **.0915**.

t-stats: t_{a1}=|**2.040435**|**> 1.96 (reject H$_0$) ;** t_{a2}=|**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^F_{t+1}

E[$e_{f,t}$] = **.0069** + **.2159** $(I_{MY,t} - I_{US,t})$ + **.0915** $(y_{MY,t} - y_{US,t})$

Forecasts for next month (t+1): $E_t[I_{MY,t} - I_{US,t}]$ = 3%

$E_t[y_{MY,t} - y_{US,t}]$ = 2%.

$E_t[e_{f,t+1}]$ = **.0069** + **.2159** * (.03) + **.09157** * (.02) = **.0152**.

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

Example 2 (continuation): Out-of-sample Forecasting w/Ad-hoc Model

1. Forecast S^F_{t+1} (continuation)

$E_t[e_{f,t+1}]$ = **.0152**.

Suppose S_t = **3.1021 MYR/USD**

S^F_{t+1} = **3.1021 MYR/USD** * (1 + **.0152**) = **3.1493 MYR/USD**.

2. Forecast Evaluation

Suppose S_{t+1} = **3.0670** MYR/USD.

$\varepsilon_{t+1} = S^F_{t+1} - S_{t+1}$ = **3.1493** – **3.0670** = 0.0823.

Overtime, we will get Q forecast errors and, then, we will compute the MSE. Again, we will compare the MSE to the MSE of the RW Model. ¶

• 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.

• Right Evaluation Metric?

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)

$F_{t,1-mo}$ = .7335 USD/CAD

$E_{FS,t}[S_{t+1-mo}]$ = **.7342 USD/CAD**.

• Sternin's strategy: Buy CAD forward if FS forecasts > $F_{t,1\text{-month}}$.

Based on the FS forecast, Sternin buys CAD forward at $F_{t,1\text{-month}}$ = .7335.

(A) Suppose that S_{t+1-mo} = **.7390 USD/CAD**.

MAE_{FS} = |**.7390** – **.7342**| = .0052 USD/CAD.

Sternin makes a profit: **.7390** – **.7335** = .055 USD/CAD.

(B) Suppose that S_{t+1-mo} = **.7315 USD/CAD**.

MAE_{FS} = |**.7315** – **.7342**| = .0027 USD/CAD (smaller!)

Sternin takes a loss: **.7315** – **.7335** = -.0020 USD/CAD. ¶

Remark: Getting direction right is more important. Different metric?

Technical Analysis Approach

• Based on a small set of the available data: Past price information.

Q: Why ignore fundamentals, say, $(I_{d,t} - I_{f,t})$?
EMH: FX market "discounts" public information regarding fundamentals

• TA looks for the repetition of specific price patterns.

• 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.

• Popular TA models:
  - Moving Averages (MA)
  - Filters
  - Momentum indicators.
  - Bollinger 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).

• We will review the first three models: MA, Filters and Momentum.

(1) *MA models*

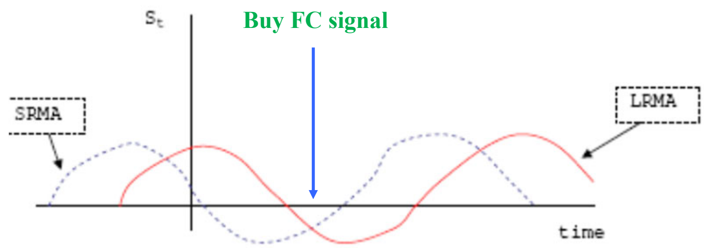
MA model: Smooth erratic daily swings of S_t.

Define S_t^{MA} as SMA:

$$S_t^{MA} = (S_t + S_{t-1} + S_{t-2} + \ldots + S_{t-(Q-1)})/Q$$

Double MA system uses two S_t^{MA}'s: Long-run MA, with Q = Q_L &
Short-run MA, with Q = Q_S, $Q_L > Q_S$.

LRMA always lags the SRMA (LRMA gives smaller weights to recent S_t).



Buy FC signal: When SRMA crosses LRMA from below.

Sell FC signal: When SRMA crosses LRMA from above.

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

(2) *Filter models*

Filter = **X**, a *percentage* that helps to spot a trend.

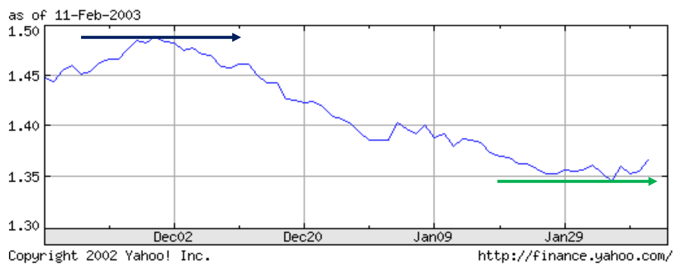
Sell signal: S_t falls **X%** below the previous peak.

Buy signal: S_t rises **X%** above its most recent trough.

Idea:

When S_t reaches a peak ⇒ Sell FC

When S_t reaches a trough ⇒ Buy FC.



Key: Identifying a peak/trough. The filter does it:

When S_t moves **X%** above (below) its most recent high (low), we have identified a peak (through).

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

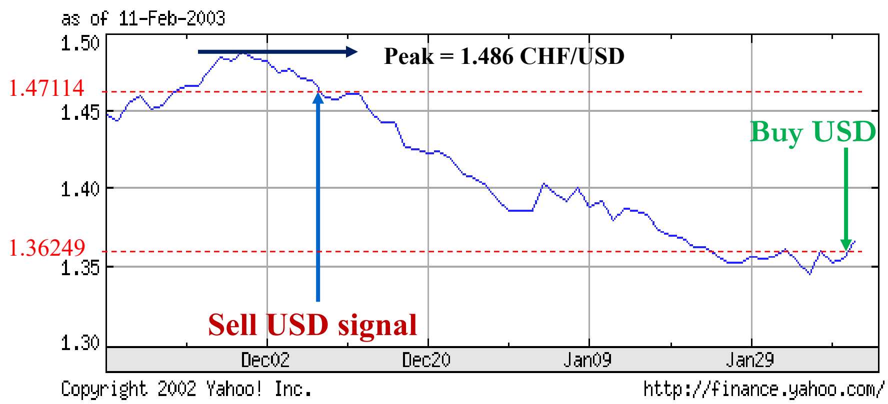
Peak = 1.486 CHF/USD (X = CHF .01486)

⇒ When S_t crosses 1.47114 CHF/USD, **Sell USD**

Trough = 1.349 CHF/USD (X = CHF .01349)

⇒ When S_t crosses 1.36249 CHF/USD, **Buy USD**

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



Peak = 1.486 CHF/USD (X = CHF .01486)

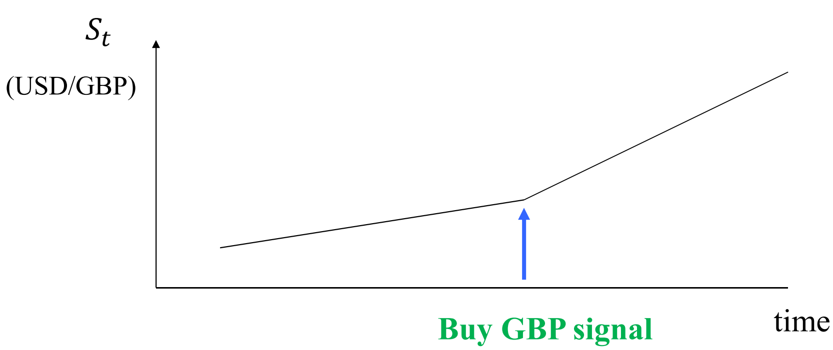
⇒ When S_t crosses 1.47114 CHF/USD, **Sell USD**

(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 FC signal: When S_t climbs at increasing speed.
Sell FC signal: When S_t decreases at increasing speed.



• TA Newer Models:
In MA and filter models, we need to select a parameter (Q & X). Subjective selection: Two TA practitioners using the same model may generate different signals.

Newer TA methods 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.
• Economists have a negative view of TA: TA runs against EMH.

\- *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): Apparent success of TA in FX markets is influenced by CB intervention.
  ◦ Lo (2004): Markets are adaptive efficient: TA may work for a while.
  ◦ Ohlson (2004): Even in-sample, profitability has declined (≈ 0 profits by the 1990s).
  ◦ Park and Irwin (2007): Problems with TA studies: Data snooping, ex-post selection of trading rules, estimation of risk & transaction costs.