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:

$E_t[S_{t+T}]$ ⇒ Expectation of S_{t+T} taken at time t.

• It is easier to predict changes. We will concentrate on $E_t[s_{t+T}]$.

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

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

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

• **Assumptions Needed for X_{t+T}**

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

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

⇒ We'll use Z_t to forecast the future S_{t+T}: $E_t[S_{t+T}] = g(Z_t)$

Example: What is $g(Z_t)$?

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

1. Model for S_t

$$E_t[s_{t+1}] = s^F_{t+1} = (S^F_{t+1}/S_t) - 1 \approx I_{d,t+1} - I_{f,t+1}$$

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

$$E_t[S_{t+1}] = S_t \text{ x } [1 + s^F_{t+1}] = S_t \text{ x } [1 + (I_{US,t+1} - I_{UK,t+1})]$$

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

- $I_{US,t} = \alpha^{US}_0 + \alpha^{US}_1 I_{US,t-1}$
- $I_{UK,t} = \alpha^{UK}_0 + \alpha^{UK}_1 I_{UK,t-1}$

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

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

$$= S_t \text{ x } [1 + \alpha^{US}_0 + \alpha^{US}_1 I_{US,t-1} - \alpha^{UK}_0 - \alpha^{UK}_1 I_{UK,t-1}).$$ ¶

• 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 (based on data that incorporates only past prices).

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.)

    ⇒ 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.)

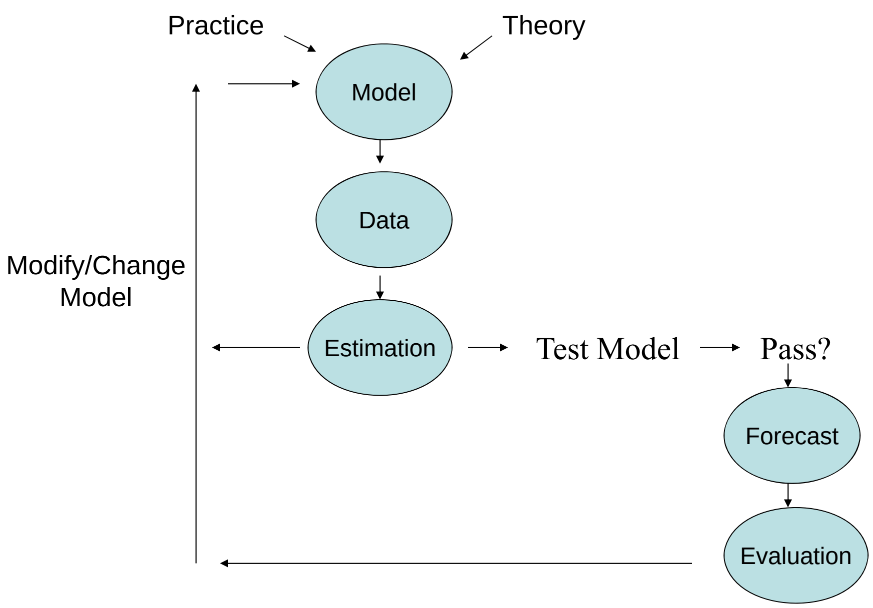
(3) Estimation of model, if needed (regression, other methods)

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

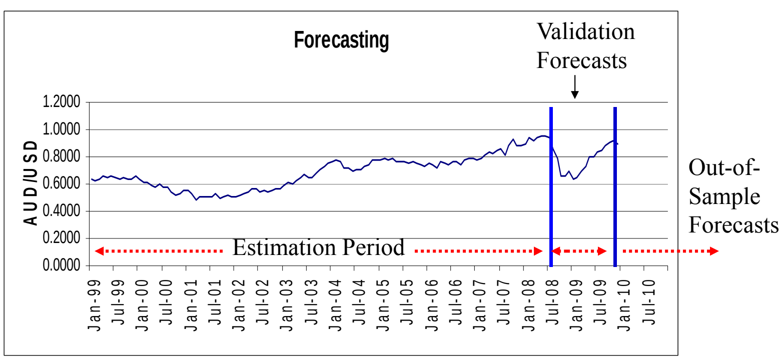
(5) Evaluation. Forecasts are evaluated. If forecasts are very bad, model must be changed.

⇒ MSE (Mean Square Error) and MAE (Mean Absolute Error) are measures used to asses forecasting models.

Fundamental Forecasting: Process



Fundamental Forecasting: Usual Estimation Process



- 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.

Example: In-sample PPP forecasting of USD/GBP

PPP equation for USD/GBP changes:

$$E_t[s_{t+1}] = s^F_{t+1} \approx I_{US,t+1} - I_{UK,t+1} \quad \Rightarrow \quad E_t[S_{t+1}] = S^F_{t+1} = S_t \text{ x } [1 + s^F_{t+1}]$$

Data: Quarterly CPI series for U.S. and U.K. from 1996:1 to 1997:3.

US-CPI: 149.4, 150.2, 151.3

UK-CPI: 167.4, 170.0, 170.4

$S_{1996:1}$= 1.5262 USD/GBP.

$S_{1996:2}$= 1.5529 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**.

$S^F_{1996:2} = S^F_{1996:1} \text{ x } [1 + s^F_{1996:2}]$ = 1.5262 USD/GBP x [1 + (**-.01018**)] =

= 1.51066 USD/GBP.

- **Example (continuation)**:

$S^F_{1996:2}$= **1.51066** USD/GBP.

2. Forecast evaluation (Forecast error: $S^F_{1996:2}$-$S_{1996:2}$)

$\varepsilon_{1996:2} = S^F_{1996:2} - S_{1996:2}$ = **1.51066** – 1.5529 = -0.0422.

For the whole sample:

Date	CPI U.S.	CPI U.K.	In-Sample Forecast (S^F_{t+1})	Actual (S_t)	Forecast Error $\varepsilon_{t+1}=S^F_{t+1}-S_{t+1}$
1996:1	149.4	167.4	1.5262	1.5262	-
1996:2	150.2	170.0	1.5107	1.5529	-0.0422
1996:3	151.3	170.4	1.5182	1.5653	-0.0471
1996:4	152.6	171.5	1.5214	1.7123	-0.1909
1997:1	153.2	173.3	1.5114	1.6448	-0.1334
1997:2	154.1	176.0	1.4968	1.6650	-0.1682
1997:3	155.6	179.0	1.4858	1.6117	-0.1259

MSE: $[(-0.0422)^2 + (-0.0471)^2 + ... + (-0.1259)^2]/6 = 0.017063278$

Note: Not a true forecasting model.

Example: Out-of-sample Forecast: $E_t[S_{t+T}]$

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

$E_t[s_{t+1}] = s^F_{\ t+1} = (E_t[S_{t+1}]/S_t) - 1 \approx I_{d,t} - I_{f,t}$.

Using the above information we can predict $S_{1996:3}$:

1. Forecast $S^F_{1996:3}$

$s^F_{1996:3} = I_{US,1996:2} - I_{UK,1996:2} = .00535 - .01553 = \mathbf{-.01018}$.

$S^F_{1996:3} = S_{1996:2} \times [1 + s^F_{1996:3}] = 1.5529 \times [1 + (\mathbf{-.01018})] = \mathbf{1.53709}$

2. Forecast evaluation

$\varepsilon_{1996:3} = S^F_{1996:3} - S_{1996:3} = \mathbf{1.53709} - 1.5653 = -0.028210$.

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:

$I_{US,t} = \alpha^{US}_0 + \alpha^{US}_1 I_{US,t-1} + \varepsilon_{US,t}$.

$I_{UK,t} = \alpha^{UK}_0 + \alpha^{UK}_1 I_{UK,t-1} + \varepsilon_{UK,t}$.

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

$a^{US}_0 = \mathbf{.0036}$, $a^{US}_1 = \mathbf{.64}$, $a^{UK}_0 = \mathbf{.0069}$, and $a^{UK}_1 = \mathbf{.43}$.

Therefore,

$I^F_{US,1996:3} = \mathbf{.0036} + \mathbf{.64} \times (.00535) = .007024$

$I^F_{UK,1996:3} = \mathbf{.0069} + \mathbf{.43} \times (.01553) = .013578$.

$s^F_{1996:3} = I^F_{US,1996:3} - I^F_{UK,1996:3} = .007024 - 013578 = \mathbf{-.00655}$.

$S^F_{1996:3} = 1.5529$ USD/GBP x $[1 + (\mathbf{-.00655})] = \mathbf{1.5427}$ USD/GBP.

$\varepsilon_{1996:3} = S^F_{1996:3} - S_{1996:3} = \mathbf{1.5427} - 1.5653 = -0.0226$.

Example: Exchange Rate Forecasts

US Excel Regression Results:

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 (continuation): Inflation Forecasts - UK 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

← $I_{UK,t-1}$ 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

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

Forecast monthly MYR/USD changes with the following model:

$$s_{MYR/USD,t} = a_0 + a_1\,(I_{MYR} - I_{USD})_t + a_2\,(y_{MYR} - y_{USD})_t + \varepsilon_t$$

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: a_i=0

$t_{a1}=a_1/SE(a_1)$ = **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 (continuation): Out-of-sample Forecasting w/Ad-hoc Model

$$s_{MYR/USD,t} = a_0 + a_1\,(I_{MYR} - I_{USD})_t + a_2\,(y_{MYR} - y_{USD})_t + \varepsilon_t$$

0. Model Evaluation

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

t-stats: $t_{a1} = |\mathbf{2.040435}| > \mathbf{1.96}$ (reject H_0)

$t_{a2} = |\mathbf{1.772428}| < \mathbf{1.96}$ (cannot 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}

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

Forecasts for next month (t+1): $E_t[INF_{t+1}]$= 3% and $E_t[INC_{t+1}]$= 2%.

$E_t[s_{MYR/USD,t+1}]$ = **.0069** + **.2159** x (.03) + **.09157** x (.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^F_{t+1} (continuation)

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

Suppose S_t=3.1021 MYR/USD

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

2. Forecast evaluation

Suppose S_{t+1}= **3.0670**

$\varepsilon_{t+1} = S^F_{t+1} - S_{t+1}$ = **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.
  - ⇒ 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 stragey: buy CAD forward if FS forecasts CAD appreciation.)

Based on the FS forecast, Ms. Sternin decides to buy CAD forward at .

(A) Suppose that the CAD appreciates to .7390 USD/CAD.

MAE_{FS} = .7390 - .7342 = .0052 USD/CAD.

Sternin makes a profit of .7390 - .7335 = .055 USD/CAD.

(B) Suppose that the CAD depreciates to .7315 USD/CAD.

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

Sternin takes a loss of .7315 - .7335 = -.0020 USD/CAD. ¶

Technical Analysis Approach

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

⋄ TA does not pay attention to fundamentals (say, $I_{d,t}$ - $I_{f,t}$). The market efficiently "discounts" public information regarding fundamentals.

⇒ No need to research or forecast fundamentals.

⋄ TA looks for the repetition of history (specific price patterns)

⇒ Discovering these patterns is an art (not science).

⋄ TA believes that assets move in *trends*. TA attempts to discover *trends* ("the trend is your friend") and *turning points*.

⇒ Based on these trends, TA generates signals.

⋄ 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.

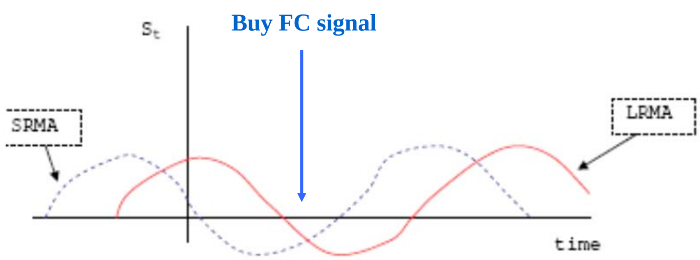
These are well-known (& old!) models that produce *mechanical rules* – i.e., produce objective signals.

(1) *MA models*

The goal of MA models is to smooth the erratic daily swings of FX to signal major trends.

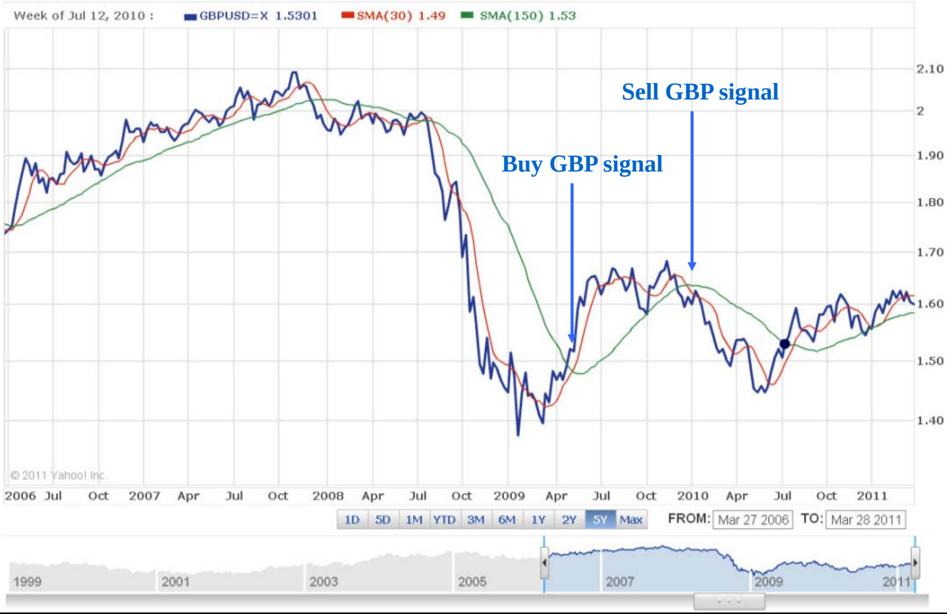
The *double MA system* uses two MA: Long-run MA and Short-run MA.

LRMA will always lag a SRMA (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 (red=30 days; green=150 days)



(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:

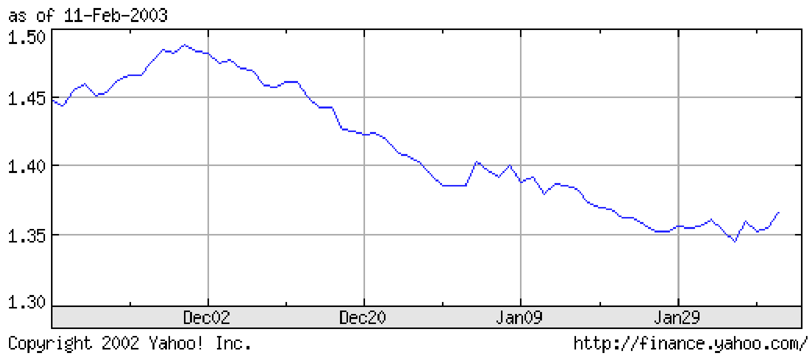
When S_t reaches a peak ⇒ Sell FC

When S_t reaches a trough ⇒ 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)



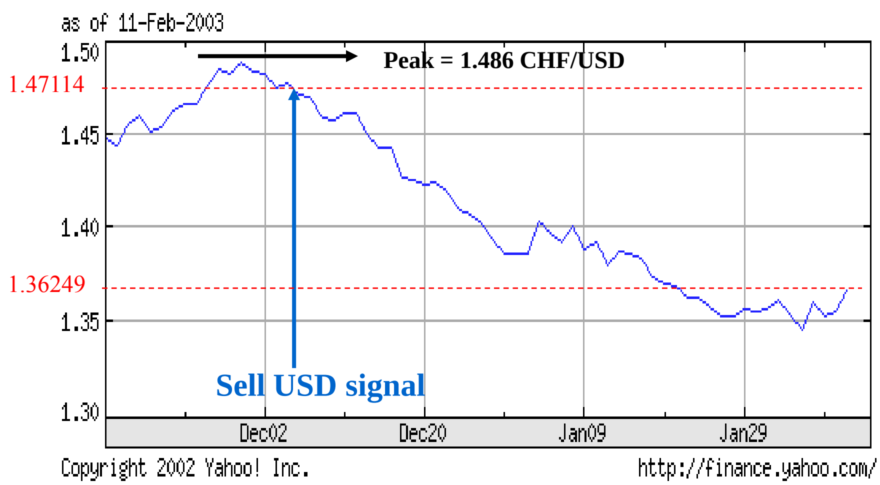
Peak = 1.486 CHF/USD (X = CHF .01486)

⇒ 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)

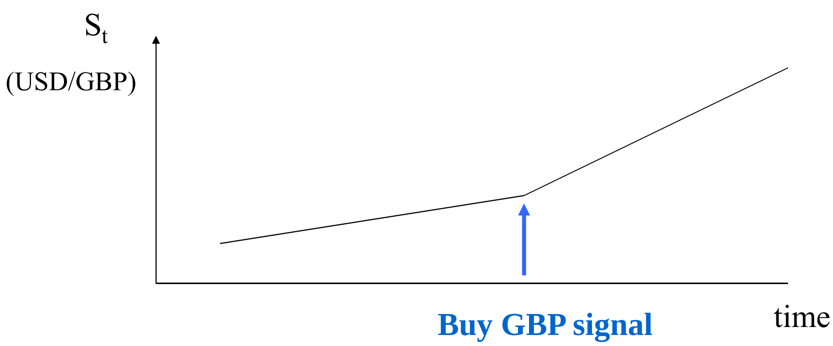
⇒ When S_t crosses 1.47114 CHF/USD, Sell USD

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



• TA: Newer Models

• In both models, the TA practitioner needs to select a parameter (Q and X). This fact can make to TA practitioners using the same model, but different parameters, to generate different signals.

• To solve this problem, there are several newer TA methods that use more complicated mathematical formulas to determine when to buy/sell, without the subjectivity of selecting a parameter.

• 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). k support for TA.

• 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* – Informal Evidence

◊ RW model: A good forecasting model.

◊ Many economists have a negative view of TA:

⇒ TA runs against market efficiency.

◊ Lo (2004) suggests that markets are adaptive efficient (AMH, adaptive market hypothesis): It may take time, but eventually, the market learns and profits should disappear.

⇒ Some TA methods may be profitable for a while.

- *For TA* – Informal Evidence

◊ The marketplace is full of TA newsletters and TA consultants (somebody finds them valuable & buys them).

◊ A survey of FX traders by Cheung and Chinn (2001) found that 30% of the traders are best classified as technical analysts.

• Technical Approach: Evidence

Academic research:

◊ Related to filter models in the FX market. Sweeney (1986): Simple filter rules generated excess returns (1973-1980). A 1% filter rule had a return of 2.8%, while a buy-and-hold strategy had a 1.6% return.

◊ TA in FX market: In general, in-sample results tend to be good –i.e., TA is profitable–, but in terms of forecasting –i.e., out-of-sample performance– the results are weak.

◊ LeBaron (1999) speculates that the apparent success of TA in the FX market is influenced by CB intervention.

◊ Ohlson (2004) finds that the profitability of TA strategies in the FX market have significantly declined over time, with about zero profits by the 1990s.

◊ Park and Irwin (2007) survey the TA recent literature in different markets. They report that out of 92 modern academic papers, 58 found that TA strategies are profitable. Park and Irwin point out problems with most studies: data snooping, ex-post selection of trading rules, difficulties in the estimation of risk and transaction costs.