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9/25 - Last Lecture

FX determination: $S_t = f(i_{DC}-i_{FC}, I_{DC}-I_{FC}, y_D-y_F$, other)
Not very successful to explain S_t –especially, in the short-run
PPP (Absolute and Relative): Rejected
IFE: Rejected
Q: What determines S_t in the short-run?
A: Still an open question. Random Walk Model for S_t has a good forecasting performance.

This Lecture

Q: Can we forecast S_{t+T}?
A: It seems very difficult. But, firms and "experts" constantly try. In this class, we will also try.

Chapter 9 - Forecasting Exchange Rates

• Brief Review and Notation

A forecast is an expectation: $E_t[S_{t+T}]$ ⇒ Expectation of S_{t+T} taken at time t ("*today*").

(Remember, in statistics, the expectation is an expected value. Think of it as an average.)

In general, it is easier to predict changes. In this class, we will concentrate on $E_t[e_{f,t+T}]$.

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

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

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

Example: For the PPP model, X_t = Inflation rate differentials ($I_{d,t} - I_{f,t}$):

$$f(X_t) = I_{d,t} - I_{f,t}$$

• Main Forecasting Methods

There are two pure approaches to forecasting FX rates:
(1) The *fundamental approach* (based on data considered fundamental).
(2) The *technical approach* (based on data that incorporates only past prices).

Method I: Fundamental Approach

• We generate $E_t[S_{t+T}] = f(X_t)$, where X_t is a dataset regarded as *fundamental* economic variables:
GNP growth rate, Current Account, Interest rates, Inflation rates, Money growth rate, etc.

• In general, the fundamental forecast is based on an *economic model* (PPP, IFE, combinations).

⇒ the economic model tells us 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 involves several steps:

(1) Selection of Model (for example, PPP model) used to generate the forecasts.

(2) Collection of S_t, X_t (in the case of PPP, exchange rates and CPI data needed.)

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

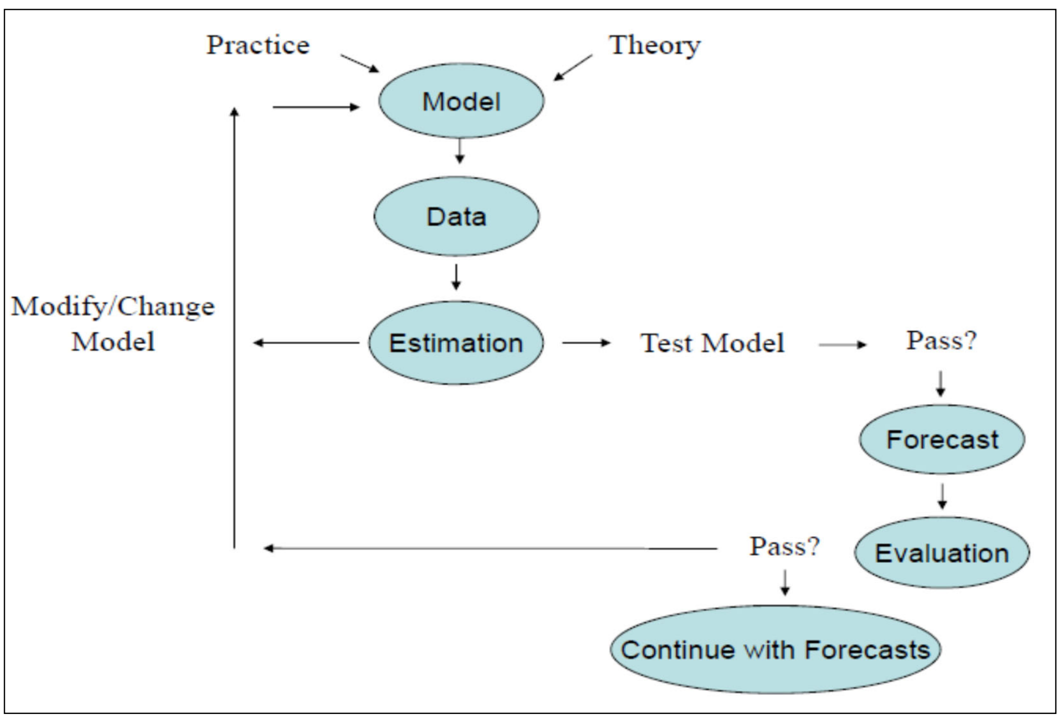
(4) Generation of forecasts based on estimated model. Assumptions about X_{t+T} may be needed.

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

⇒ MSE (Mean Square Error) is a measure used to asses forecasting models.

Exhibit 9.1 shows a typical process to build out-of-sample forecasts model.

Exhibit 9.1
Fundamental Forecasting: Process for Building Forecasting Model



Example: Forecasting S_{t+T} with Relative PPP ($E_t[S_{t+T}]$)

Formulas needed:

Economic Model (PPP): $e_{f,t} = \frac{S_{t+1}}{S_t} - 1 \approx I_{d,t} - I_{f,t}$

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

Forecasting S_{t+1}: $E_t[S_{t+1}] = S^F_{t+1} = S_t * [1 + e^F_{f,t+1}] = S_t * [1 + (I_{d,t+1} - I_{f,t+1})]$

Forecast error: $\varepsilon_{t+1} = S_{t+1} - S^F_{t+1}$ (quality of forecast)

Mean Square Error = MSE = $[(\varepsilon_{t+1})^2 + (\varepsilon_{t+2})^2 + (\varepsilon_{t+3})^2 + ... + (\varepsilon_{t+Q})^2]/Q$ (evaluation measure)

Notice that at time t, we do not know $I_{d,t+1}$ & $I_{f,t+1}$. We need a model or assumptions to forecast $E_t[I_{d,t+1}]$ & $Et[I_{d,t+1}]$.

Example (continuation): Forecasting S_{t+1} with Relative PPP ($E_t[S_{t+1}]$)

It's **February 2023**. We want to forecast March 2023 SEK/USD exchange rate (SEK = Swedish Kronor) using Relative PPP. That is, based on data available on 2023:2, we forecast, $S_{t=2023:3}$ ($S^F_{2023:3}$). This type of one period ahead forecast is called *one-step-ahead forecast*.

• *Forecasting Model*

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

• *Data*

We have CPI data and S_t data from Jan. 2023 to Feb. 2023. We want to forecast $S_{t=March, 23}$.

We have already done: (1) Selection of Model; (2) Collection of S_t, X_t; and (3) No estimation is needed. We need to do (4) Generation of forecasts based on model and (5) Evaluation of forecasts.

Date	CPI_{SWED}	CPI_{US}	S_t	I_{SWED}	I_{US}		$\varepsilon_{t+1}=S_{t+1}-S^F_{t+1}$
1/1/2023	136.1820	300.356	10.3975			1.9334	-
2/1/2023	137.6847	301.509	10.4492	**0.0110**	**0.0038**	**1.9512**	-
3/1/2023	138.4708	301.744	10.4763	0.0057	0.0008	1.9318	**-0.0215249**
4/1/2023	139.1143	303.032	10.3484	0.0046	0.0043	1.9718	0.0312088

• *Generation of forecasts* (GF)

Calculations for the 2023:3 forecast:

GF.1. Inflation rates

$I_{SWED,2023:2} = (CPI_{SWED,2023:2}/CPI_{SWED,2023:1})$ - 1 = (137.6847/136.1820) - 1 = **0.0110**.

$I_{US,2023:2} = (CPI_{US,2023:2}/CPI_{US,2023:1})$ - 1 = (301.509/300.356) - 1 = **0.0038**.

GF.2. We need a forecast for $I_{SWED,2023:3}$ - $I_{US,2023:3}$

RW forecast: Last year inflation rate is a good predictor of this year inflation rate –i.e., $E_t[I_{t+1}] = I_t$

Then,

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

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

GF.3. Now, we can predict $e_{f,t=2023:3}$ and $S_{t=2023:3}$

$E_{t=2023:2}[e_{f,t=2023:3}] = \boldsymbol{e^F_{f,2023:3}} = I_{SW,2023:2} - I_{US,2023:2}$ = **.0110** – **.00338** = **0.0072**.

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

• *Evaluation of forecasts* (EVF)

EVF.1. Next month, in 2023:3, we will compute the forecast error, $\varepsilon_{2023:3}$:

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

For comparison purposes, at the end of 2023:3, we can also generate a forecast error for the RW Model:

$\boldsymbol{\varepsilon^{RW}_{2023:3}}$ = $\mathbf{S_{2023:3}}$ – $\mathbf{S_{2023:2}}$ = **10.4763** – **10.4492** = **0.0271**

EVF.2. Then, we repeating this one-step-ahead forecasting process until 2024:3. That is, we generate 14 one-step-ahead forecasts. By 2024:4, we will compute 14 forecasts errors, and, then, the MSE for the PPP and RW forecasts errors.

Date	**S_t**	$I_{SW} - I_{US}$	$\boldsymbol{S^F_{t+1}}$	ε_{t+1}	$(\varepsilon_{t+1})^2$	$\boldsymbol{S^{F,RW}_{t+1}}$	$\boldsymbol{\varepsilon^{RW}_{t+1}}$	$(\boldsymbol{\varepsilon^{RW}_{t+1}})^2$
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**

Calculating the MSE for the PPP and RW models 2023:3-2024:4 period:
MSE^{PPP} = [(**-0.0244**)^2 + (-0.1319)^2 + …. + (0.4227)^2]/14 = **0.06455**

EVF.3 Compare the MSE of the PPP forecasting model with the RWM. Under the RWM: $E_t[S_{t+1}] = S_t$
$\varepsilon_{2007:3} = S_{2007:3} - S^F_{2007:3} = S_{2007:3} - S_{2007:2}$ = 1.9318 - 1.9512 = -0.0194.
$\varepsilon_{2007:4} = S_{2007:4} - S^F_{2007:4} = S_{2007:4} - S_{2007:3}$ = 1.9718 - 1.9318 = 0.0400.
MSE^{RW} = [(**-0.0271**)^2 + (**-0.1279**)^2 + … + (0.4045)^2] /14 = **0.06058**

For these forecasts, on average, the RW model does better than the PPP model. ¶

Example: Forecasting FX with an Ad-hoc Model
A U.S. company uses an economic linear model to forecast monthly exchange rates (USD/GBP):
Economic Regression Model:

$$e_{f,t} = a_0 + a_1\, INF_t + a_2\, INT_t + a_3\, INC_t + \varepsilon_t, \qquad (*)$$

INF_t: inflation rates differential between U.S. and the U.K.
INT_t: interest rates differential between U.S. and the U.K.
INC_t: income growth rates differential between U.S. and the U.K.

Objective: Calculate $E_t[e_{f,t+1}]$
• *Forecasting Model*

$$E_t[e_{f,t+1}] = a_0 + a_1\, E_t[INF_{t+1}] + a_2\, E_t[INT_{t+1}] + a_3\, E_t[INC_{t+1}].$$ (Recall: $E_t[\varepsilon_{t+1}] = 0$).

Inputs for the forecast: 1) a_0, a_1, a_2, a_3 (estimated through a regression).
2) $E_t[INF_{t+1}]$ and $E_t[INC_{t+1}]$ (potential problem!)

• *Data*
Income growth rates, interest rates, inflation rates and exchange rates. Suppose we have quarterly data from 1978 to 2008 (21 years).
Suppose $S_{2008:IV}$ = **1.7037 USD/GBP**.

• *Estimation*

We run a regression to estimate (*). Excel output:

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.216036
R Square	0.046672
Adjusted R Square	0.022434
Standard Error	0.050911
Observations	122

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.014973	0.004991	1.925622	0.129173
Residual	118	0.305851	0.002592		
Total	121	0.320825			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.01082	0.007553	-1.43285	0.154545	-0.02578	0.004134
INF_t	0.648128	0.547068	1.184732	0.238504	-0.43521	1.731471
INT_t	-0.00482	0.002188	**-2.20088**	0.029691	-0.00915	-0.00048
INC_t	**0.000945**	0.001613	0.585963	0.559019	-0.00225	0.00414

Analysis:

t-statistics: only the interest rate differential coefficient is bigger than two (in absolute value).

R^2 = .047 (INF, INT & INC explain 4.7% of the variability of changes in the USD/GBP).

(Note: It doesn't look like a great model, but we'll use it anyway.)

• *Generation of forecasts*

i. Suppose we have the following forecasts for next month:

$E_t[INF_{t+1}]$ = **1.68**%, $E_t[INT_{t+1}]$ = -2.2%, $E_t[INC_{t+1}]$ = 1.23%.

Then,

$E_t[e_{f,t+1}]$ = -.010802 + .6481 * (**.0168**) + (-0.00482) * (-.022) + **.000945** * (0.0123) = **0.000204**.

⇒ The USD is predicted to depreciate 0.02% against the USD next month.

ii. Now, we can forecast S^F_{t+1}:

$E_t[S_{t+1}] = S^F_{t+1} = S_t * (1+ E_t[e_{f,t+1}])$ = **1.7037 USD/GBP** * (1.**000204**) = **1.704048 USD/GBP**.

• *Evaluation of forecasts*

Suppose $S_{2009:I}$ = **1.5239 USD/GBP**, we can calculate the forecast error:

$\varepsilon_{t+1} = S_{t+1} - E_t[S_{t+1}]$ = **1.5239 USD/GBP** – **1.704048 USD/GBP** = -0.180148 (Model)

$\varepsilon_{t+1} = S_{t+1} - E_t^{RW}[S_{t+1}]$ = **1.5239 USD/GBP** – **1.7037 USD/GBP** = -0.179800 (RWM).

Note: The RWM forecast error is smaller, but just by a very small amount.

⇒ RWM advantage: No complicated estimation/model, very similar forecasts! ¶

• Practical Issues in Fundamental Forecasting

◊ Are we using the "right model?" (Is Linear ad-hoc model OK?)

◊ Estimation of the model. (Is linear regression fine?)

◊ Some explanatory variables are contemporaneous. We need a model to forecast these variables too.

• **Fundamental Forecasting: Evidence**

Recall the Meese and Rogoff's (1983) findings. They tested the short-term forecasting performance of different models (PPP, monetary approach, IFE, pure statistical (time series) models, and the RWM) for the four most liquid exchange rates. The RWM performed as well or better than any other model.

More recently, Cheung, Chinn and Pascual (2005) revisited the Meese and Rogoff's results with 20 more years of data. They still found the RWM to be the "best" model.

Note: The most modern approach to fundamental forecasting incorporates an attempt to forecast what the CB does to adjust interest rates. Usually, this involves the so-called "Taylor rule." Some economists claim this approach has some success over the RWM.

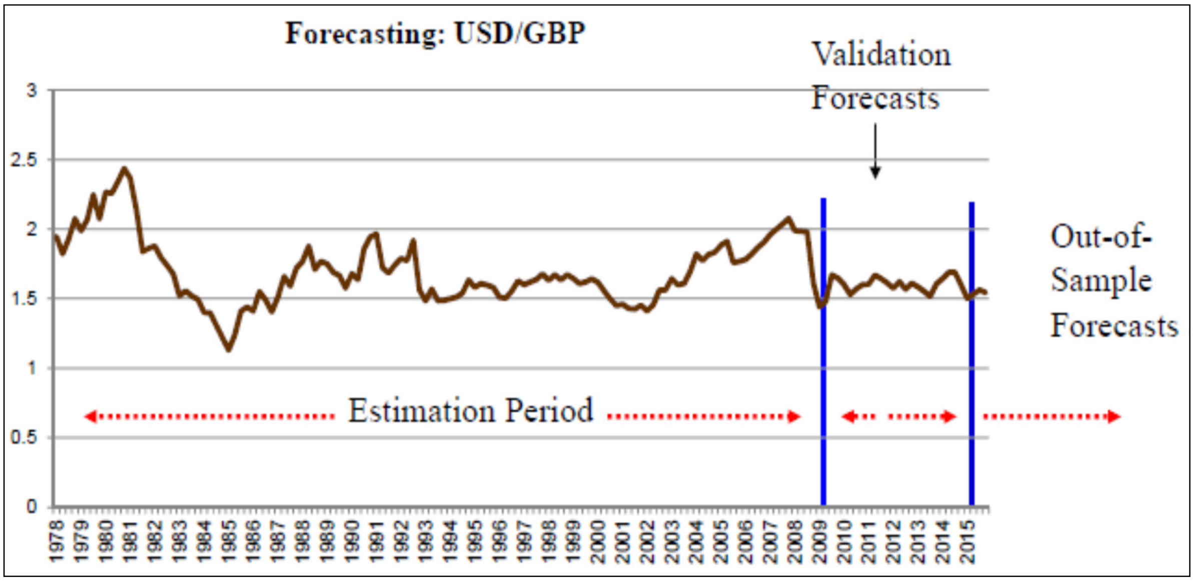
Forecasting: Note on Estimation and Generation of Out-of-sample forecasts

In general, practitioners will divide the sample in two parts: a longer sample (*estimation period*) and a shorter sample (*validation period*). The estimation period is used to select the model *and* to estimate its parameters. The forecasts made inside the estimation period are not "true forecasts," are just *fitted values*.

The data in the validation period are not used during model and parameter estimation. The forecasts made in this period are "true forecasts," their error statistics are representative of errors that will be made in forecasting the future. A forecaster will use the results from this validation step to decide if the selected model can be used to generate outside the sample forecasts.

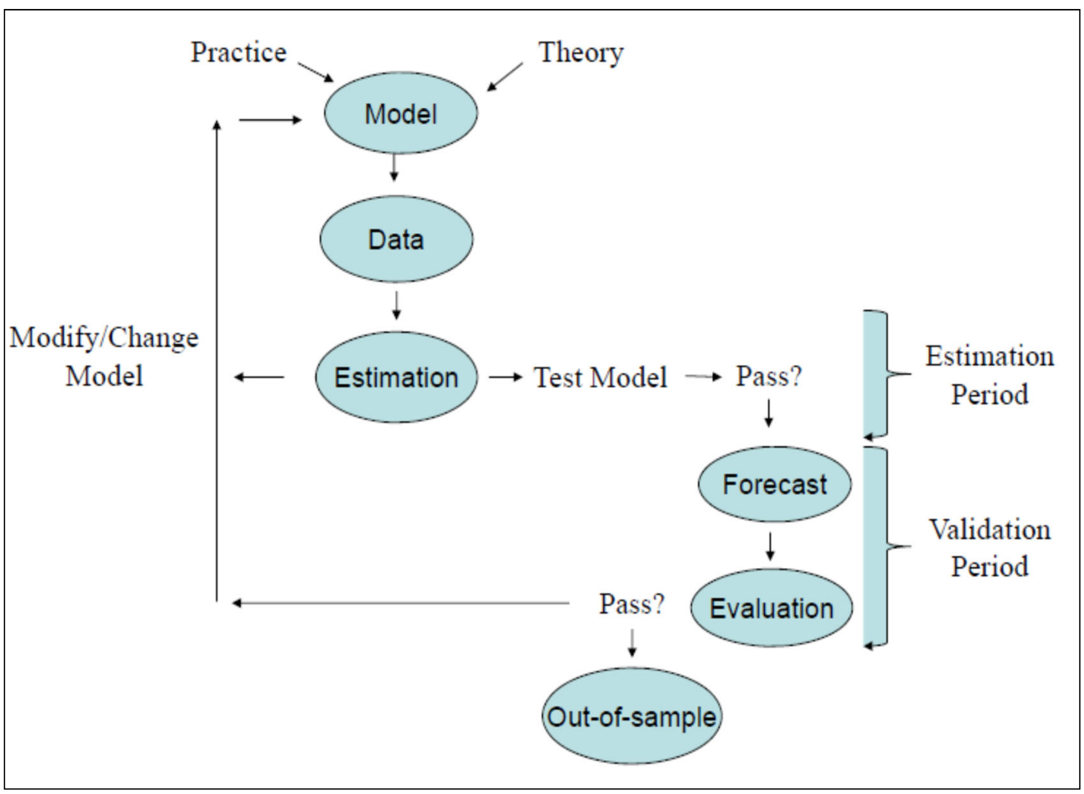
Figure 9.1 shows a typical partition of the sample. Suppose that today is March 2015 and a forecaster wants to generate monthly forecasts until January 2016. The estimation period covers from February 1978 to December 2009. Different models are estimated using this sample. Based on some statistical measures, the best model is selected. The validation period covers from January 2010 to March 2015. This period is used to check the forecasting performance of the model. If the forecaster is happy with the performance of the forecasts during the validation period, then the forecaster will use the selected model to generate out-of-sample forecasts.

Figure 9.1: Estimation, Validation & Out-of-sample Periods.



In Exhibit 9.2, we incorporate the partition of the data in the flow chart presented in Exhibit 9.1. It is easy to visualize how to generate out-of-sample forecasts.

Exhibit 9.2
Out-of-sample Forecasting: The Role of the Estimation and Validation Periods



Method II: Technical Analysis (TA) Approach

We generate $E_t[S_{t+T}] = f(X_t)$, where X_t is a small set of the available data: Past price information.

⇒ $X_t = \{S_t, S_{t-1}, S_{t-2},....\}$

◊ 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; in particular, the repetition of 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 & turning points, TA generates signals.

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

• TA: Two Popular Models

We will go over two popular well-known (& old!) models that produce *mechanical rules* –i.e., produce objective signals:

◊ *Moving Averages* (MA)

◊ *Filters*

(1) *MA model*: The goal of MA models is to smooth the erratic daily swings of FX to signal major trends. We will use the simple moving average (SMA).

An SMA is the unweighted mean of the previous Q data points:

⇒ SMA = $S_t^{MA} = (S_t + S_{t-1} + S_{t-2} + ... + S_{t-(Q-1)})/Q$

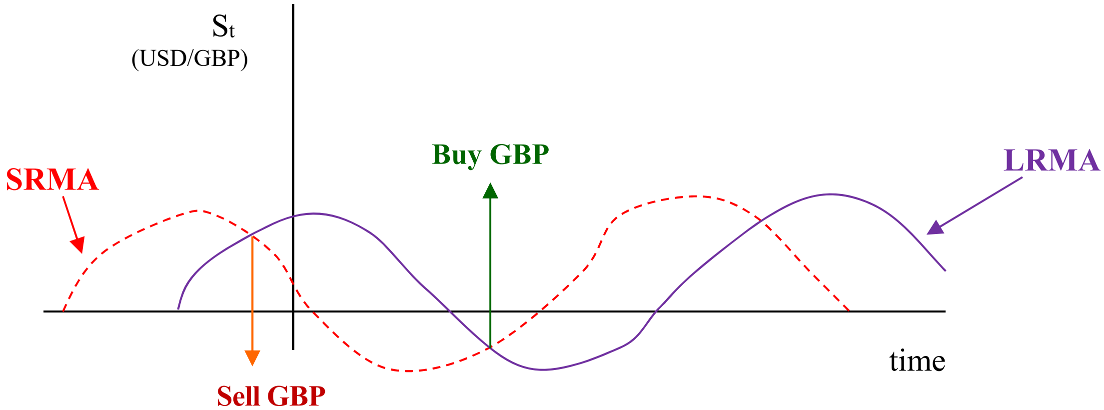
The *double MA system* uses two MA: Long-run MA (Q large, say 120 days) and Short-run MA (Q small, say 30 days). LRMA will always lag a SRMA (the LRMA gives smaller weights to recent S_t).

Every time there is a crossing, a qualitative forecast is generated.

When SRMA crosses LRMA from below ⇒ Forecast: FC to appreciate

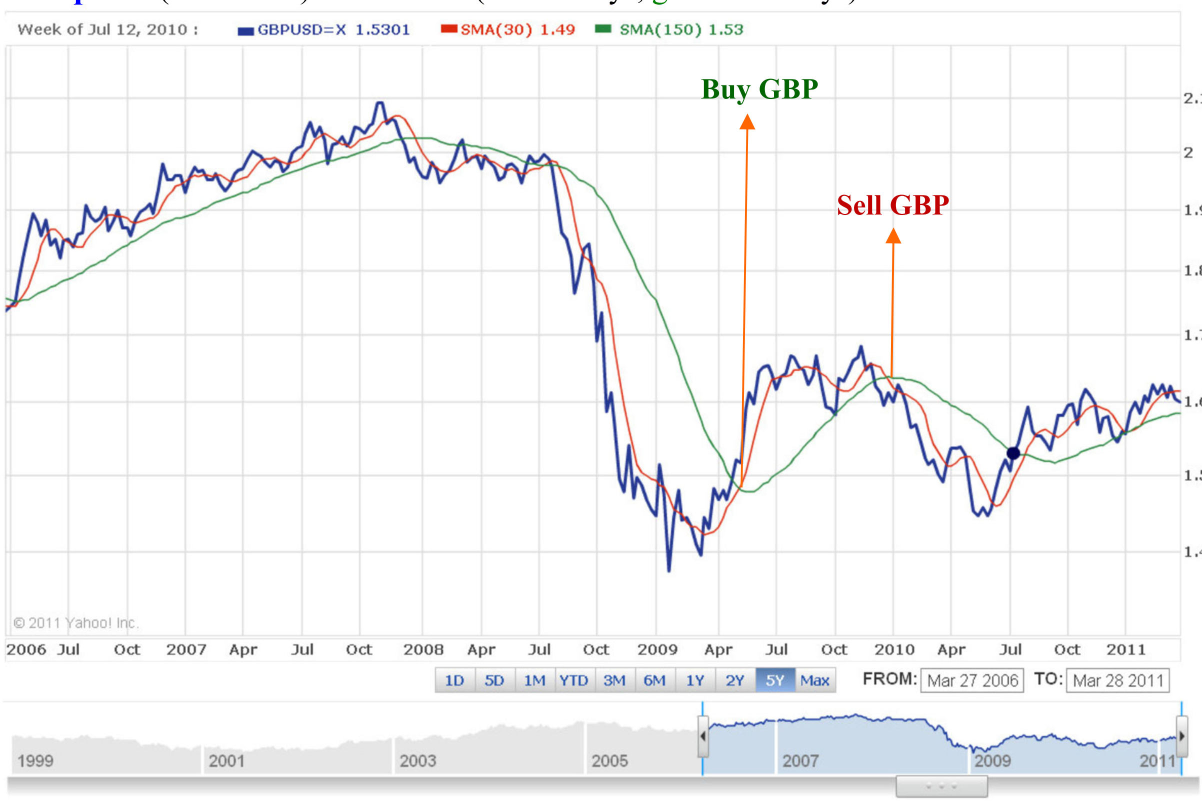
When SRMA crosses LRMA from above ⇒ Forecast: FC to depreciate.

The *double MA system* uses the two MAs to forecast changes in S_t and generate trading signals.



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).



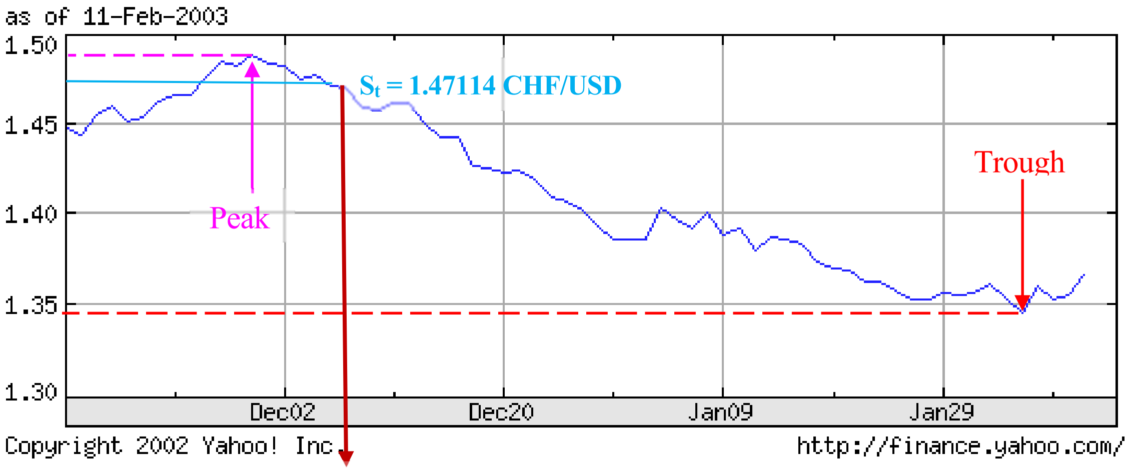
(2) *Filter models*: The filter, X, is a percentage that helps a trader forecasts a trend.
Simple Intuition:

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** ¶

• TA: Newer Models

In both 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.

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).

• TA: Summary

- ◊ TA models monitor the derivative (slope) of a time series graph.
- ◊ Signals are generated when the slope varies significantly.

• TA: Evidence

- *Against TA*

◊ Random walk model: It is a very good forecasting model.

◊ Many economists have a negative view of TA: TA runs against market efficiency (EM Hypothesis).

- *For TA*:

◊ 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.
◊ 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.

- *Academic research*:
◊ Related to filter models in the FX market. Sweeney (1986, Journal of Finance): 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., 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 the periods where there is 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, Journal of Economic Surveys) 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.

CHAPTER 9 - BONUS COVERAGE: TAYLOR RULE

According to the Taylor rule, the CB raises the target for the short-term interest rate, i_t, if:
(1) Inflation, I_t, raises above its desired level
(2) Output, y_t, is above "potential" output

The target level of inflation is positive (deflation is thought to be worse than positive inflation for the economy) The target level of the output deviation is 0, since output cannot permanently exceed "potential output."

John Taylor (1993) assumed the following reaction function by the CB:

$$i_t = I_t + \gamma\ (I_t - I_t^*) + \gamma\ y\_gap_t + r^* \qquad \text{(Equation BC.1)}$$

where y_gap_t is the output gap –a percent deviation of actual real GDP from an estimate of its potential level-, and r^* is the equilibrium level or the real interest rate, which Taylor assumes equal to 2%. The coefficients θ and γ are weights, which can be estimated (though, Taylor assumes them equal to .5).

Let I_t^* and r^* in equation BC.1 be combined into one constant term, $\mu = r^* - \gamma\ I_t^*$. Then,

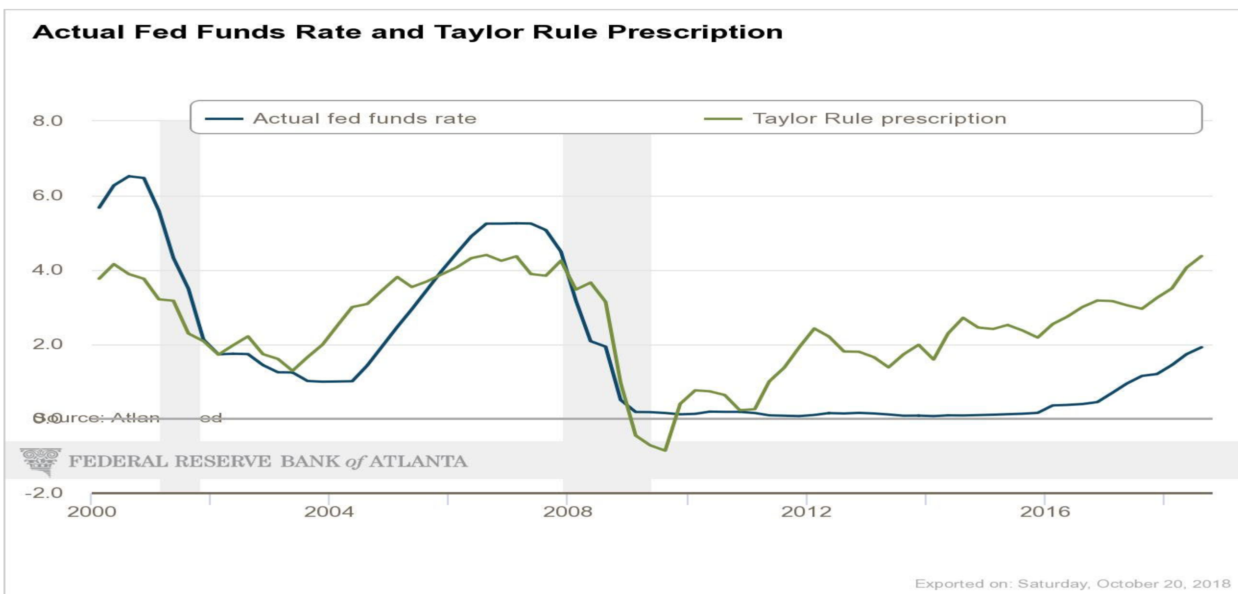
$$i_t = \mu + \lambda\ I_t + \theta\ \text{y-gap}_t,$$

where $\lambda = 1 + \gamma$. Using Taylor's assumed coefficients ($\gamma = \theta = 0.5$), $r^* = 2\%$ and $I^*=2\%$, we predict that the Fed sets interest rates according to:

$$i_t = .01 + 1.5\ I_t + 0.5\ \text{y-gap}_t.$$

We graphed this prediction ("Taylor Rule Prescription") below in Figure 9.2 for the period 2000-2018, along with the actual Fed funds rate.

Figure 9.2
Taylor Rule: U.S. Federal Fund Rate (2000 - 2018)

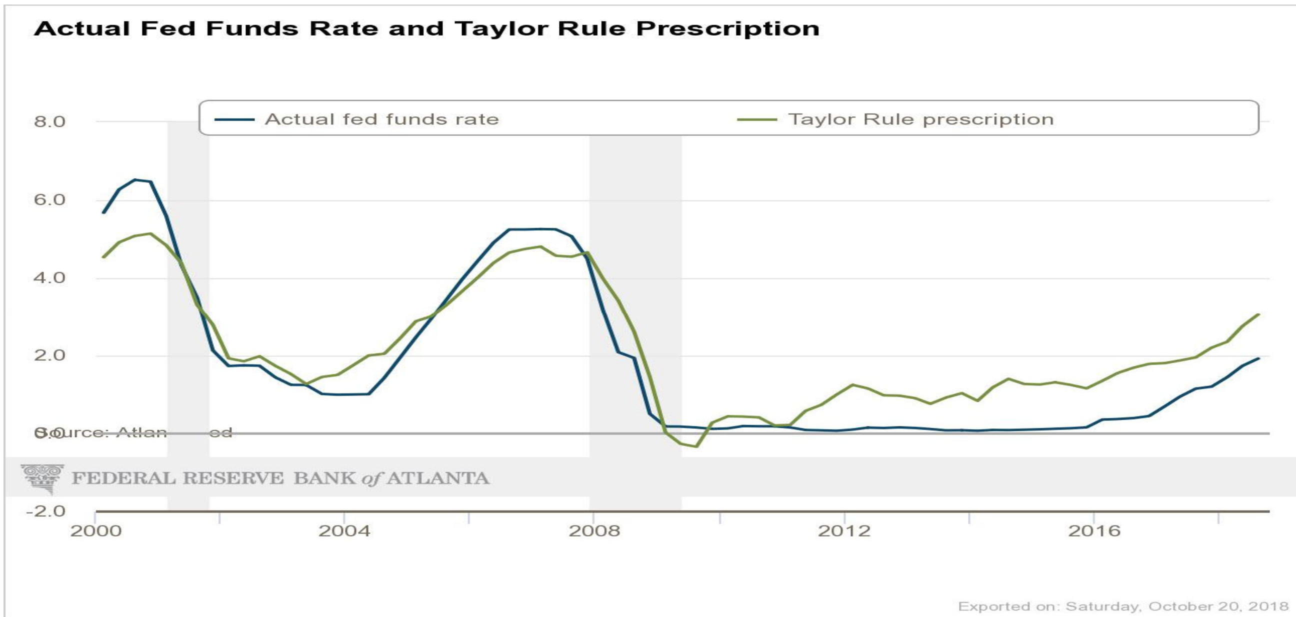


A popular variation to the Taylor rule (Equation BC.1) is to allow for gradualism in interest rate policy, reflecting the usual Central Bank practice of gradual, small adjustments in interest rates. This *modified Taylor rule* is:

$$i_{d,t} = \rho\ i_{d,t-1} + (1 - \rho)\ [r_t^* + I_{d,t} + \gamma\ (I_{d,t} - I_{d,t}^*) + \theta\ y\text{-}gap_t],$$

where ρ is the smoothing parameter. If there is no gradual adjustment (ρ=0), the modified Taylor rule, reverts to the original rule. For example, using ρ=0.5 and the previous parameter values, in Figure 9.3 we graph the Taylor Rule prediction. It looks better.

Figure 9.3
Modified Taylor Rule: U.S. Federal Fund Rate (2000 - 2018)



For many countries, whose CB monitors S_t closely, the Taylor rule is expanded to include the real exchange rate, R_t:

$$i_t = \mu + \lambda\ I_t + \gamma\ y\text{-}gap_t + \delta\ R_t.$$

Estimating this equation for the U.S. and a foreign country can give us a forecast for the interest rate differential, which can be used to forecast exchange rates.

CHAPTER 9 – BRIEF ASSESMENT

You work in Austin for a local investment bank. You have available quarterly inflation rate (I), interest rate (i), and growth rate (y) data for the U.S. and Europe from 2016:1 to 2016:4. The USD/EUR in 2016:1 was equal to 1.0821 USD/EUR, which you believe is an equilibrium exchange rate. Your job is to do quarterly forecasts of the USD/EUR exchange rate for 2017:1. The investment bank uses the following ad-hoc model:

$$s_{t+1} = S_{t+1}/S_t - 1 = .75\,(I_{d,t+1} - I_{f,t+1}) + .25\,(y_{d,t+1} - y_{f,t+1}) \qquad \text{(M1).}$$

This model is based on the monetary approach. You have the following data:

Year	$y_{US} - y_{EUR}$	I_{US}-I_{EUR}	i_{US}-i_{EUR}	S_t (EUR/USD)
2016.1	0.17%	0.4473%	-0.5012%	1.0821
2016.2	0.24%	0.6976%	-0.0593%	1.1453
2016.3	0.31%	-0.1308%	0.6773%	1.1183
2016.4	0.57%	-0.3403%	0.8381%	1.0962

To forecast **income growth rates differentials** (y_t) your firm uses the following regression model (estimated regression is attached below):

$$y_{US,t} - y_{EUR,t} = \alpha + \beta\,(y_{US,t-1} - y_{EUR,t-1}) + \varepsilon_t.$$

To forecast **inflation rates** (I) your firm uses a RW model.

(A) Use the ad-hoc model (M1) to forecasts the USD/EUR exchange rate for the period 2017:1.
(B) Use the forward rate to forecast the USD/EUR exchange rate for the period 2017:1.
(C) Use S_t^{PPP} (long-run PPP, starting with $S_{t=2016.1}$) to forecast the USD/EUR exchange rate for the period 2016:4.
(D) Use the random walk to forecast the USD/EUR exchange rate for the period 2017:1.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.196241
R Square	0.03851
Adjusted R Square	0.032185
Standard Error	1.143971
Observations	154

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	7.967219	7.967219	6.088029	0.01472
Residual	152	198.9178	1.30867		
Total	153	206.885			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	-0.03019	0.092218	-0.32737	0.743839	-0.21238
X Variable 1	0.19537	0.079181	2.467393	0.01472	0.038933