

 Last Class • Theories of FX rates determination: - Parity Conditions • PPP: LOOP for a basket of goods: Same price at home or abroad. - Absolute PPP: $\mathbf{S_t^{PPP}} = P_d / P_f$ \Rightarrow **R**_t = **S**_t $P_f / P_d = 1$. Tested with different baskets (CPI, Big Mac, Iphone) \Rightarrow **R**_t = 1 rejected by data. - Relative PPP (takes into consideration fixed transactions costs): $s_{t,T}^{PPP} \approx (I_d - I_f)$ Tested with a regression: $s_{t,T} = \alpha + \beta (I_d - I_f)_{t+T} + \varepsilon_{t+T}.$ Null hypothesis is: H₀ (Relative PPP true): $\alpha = 0$ and $\beta = 1$ H₁ (Relative PPP not true): $\alpha \neq 0$ and/or $\beta \neq 1$ \Rightarrow Rejected in the short-run, some long-run support.

Last Class
Parity Conditions (continuation)
IFE: Same "effective" return from investing at home or abroad s^{IFE}_{t,T} ≈ i_d - i_f Tested with a regression: s_{t+T} = α + β (i_d - i_f)_{t,T} + ε_{t+T}
Null hypothesis is: H₀ (Relative IFE true): α=0 and β=1 H₁ (Relative IFE not true): α≠0 and/or β≠1
⇒ Rejected in the short-run, some long-run support: "*Currencies with high interest rate differentials tend to depreciate.*"
Implication: Carry trades are, on average, profitable.

• Last Class - Parity Conditions (continuation) • EH: EH: On average, the future spot rate is equal to the forward rate. $\Rightarrow E_t[S_{t+T} - F_{t,T}] = 0$ $\mathbf{E}_{t}[S_{t+T}] = \mathbf{F}_{tT}.$ Tested with a regression: $(S_{t+T} - \mathbf{F}_{t,T})/S_t = \boldsymbol{\alpha} + \boldsymbol{\beta} \, Z_t + \boldsymbol{\varepsilon}_t,$ where Z_t represents variables used to forecast S_t , usually $(i_d - i_f)$. Null hypothesis is: H₀ (EH true): $\alpha = 0$ and $\beta = 0$. H₁ (EH not true): $\alpha \neq 0$ and/or $\beta \neq 0$. \Rightarrow Rejected. Puzzle! Usual result: $\beta < 0$ (and significant) when $Z_t = (i_d - i_f)$. But, the R^2 is very low. <u>Implication</u>: Forward rate not a good tool to forecast S_{t+T} . Risk premium?



• <u>IFE: Summary</u>:

According to IFE, S_t is set in such a way that international investors, a priori, are indifferent between investing abroad or at home. Then, carry trades are, on average, not profitable. That is,

$$s_{t,T}^{IFE} \approx i_d - i_f$$

We called this relation Uncovered IRP or UIRP.

• IFE: Evidence & Implications

No short-run evidence \Rightarrow Carry trades work (on average).

Burnside (2008): The average excess return of an equally weighted carry trade strategy, executed monthly, from **1976–2007**, was about **5% per year**. (& less risky: carry trade return volatility is lower than that of stocks).

Some long-run support:

"Currencies with high interest rate differentials tend to depreciate."

Structural Models

- We will go over two models that incorporate different views of the FX market:
 - (1) BOP approach treats exchange rates as determined in flow markets. \Rightarrow Trade, portfolio investment, and direct investment.
 - (2) Monetarist approach treats exchange rates as any other asset price.
 ⇒ Currency is another asset in an investor's portfolio.

(1) BOP Approach
Balance Of Payments (BOP)
BOP divides the flow of foreign currency to the domestic country into: *Current account* (CA): Measures the movement of good and services + unilateral transfers. *Capital Account* (KA): Measures financial transactions associated with trade + changes in the composition of international portfolios. *Official Account* (OR): Measures changes in official reserves.
⇒ BOP = CA + KA + OR.
As long as the country is not bankrupt, BOP = 0.
In general, OR is small ⇒ CA ≈ – KA.





The Macroeconomics of the BOP: Absorption Approach
In equilibrium, we can write: CA = S - [I + (G - T)],
where

s: after-tax private savings.
I: private investment.
G: government spending.
T: national taxes.

To reduce a CA deficit, one of the following must happen in equilibrium:

i. S ↑, for a given level of I and (G - T).
ii. I ↓, for a given level of S and (G - T).
iii. G - T ↓, for a given level of S and I.

Example: Japan has a (relative) high savings rate. It is argued that this is the reason behind the persistent Japanese CA surpluses. ¶

The Monetary Approach to the BOP Consider the capital account (KA):
⇒ When the OR is small, KA provides the other side of the CA.
KA is assumed to depend on the interest rate differential and S_t: KA = f(i_d - i_f, S_t).
Look at the KA: When KA > 0 (CA < 0) ⇒ A country accumulates debt or sells its current stock of foreign assets.
When KA < 0 (CA > 0) ⇒ A country reduces debt or increases its current stock of foreign assets.
Example: Japan may run a CA>0 without changes in the real value of JPY, as long as the Japanese continue to accumulate foreign assets.

• BOP Approach: Implications

First, we ignored financial flows when we analyzed the BOP. We said:

A CA deficit (surplus) is corrected with a depreciation (appreciation) of S_t .

But once we consider the capital account, this depreciation (appreciation) might not occur. Foreigners might finance the CA imbalance.

Example: Japan may have CA>0 without any change in the real JPY because the Japanese continue to accumulate foreign assets.

In the long-run the BOP approach has more precise predictions:

"Countries will not be able to finance CA imbalances forever. Then, in the long-run persistent CA deficits will create KA outflows and depreciation pressures."

(2) Monetary Approach

Exchange rates are asset prices traded in efficient markets.

• Like other asset prices, S_t is determined by *expectations*. Current trade flows are irrelevant. (Actually, they are only relevant if the signal something about the future.)

• In a typical asset approach model we have:

- Assets denominated in DC & FC.
- A high degree of capital mobility between those assets.
- S_t moves to bring equilibrium to markets.

We need to be precise about the assets an investor considers.

Example: An investor considers only domestic and foreign money. Then, only news related to these assets will move S_t .

• <u>A Simple Monetary Approach Model</u> Assets: Domestic money Foreign money. Equilibrium condition: QTM relation: $M_{S,j} V_j = P_j Y_j$ j = domestic country, foreign country. S_t : Determined by Absolute PPP (= P_d/P_f): $S_t = (V_d/V_f) * (Y_f/Y_d) * (M_{S,d}/M_{S,f}),$ V_j : Velocity of money of country j, Y_j : Real output of country j, $M_{S,j}$: Money Supply of country j (equilibrium: $M_S = L_D$ (money demand)) Recall that $x_{t,T} = (X_{t+T} - X_t)/X_t \approx \log(X_{t+T}) - \log(X_t)$ (\Rightarrow a growth rate). Assuming V_j is constant, we express the model in changes: $\Rightarrow s_{t,T} = y_{f,T} - y_{d,T} + m_{S,d,t} - m_{S,f,t}$

• <u>A Simple Monetary Approach Model</u> The simple Monetary Model produces the following model for $s_{t,T}$: $\Rightarrow s_{t,T} = y_{f,T} - y_{d,T} + m_{S,d,t} - m_{S,f,t}$.

• Monetary Approach: Implications

- A stable monetary policy –i.e., low $m_{S,d,t}$ – tends to appreciate the DC. - Economic growth –i.e., $y_{d,T} > 0$ – tends to appreciate the DC.

But, keep in mind that all variables are in relative terms.

<u>Note</u>: S_t behaves like any other speculative asset price: S_t changes whenever relevant information –about money growth & GDP growth– is released.

• Monetary Approach: Application

Example: Forecasting S_t with the simple monetarist model. <u>Model</u>:

$$s_{t,T} = y_{f,T} - y_{d,T} + m_{S,d,T} - m_{S,f,T}.$$

<u>Data</u>:

MS in the U.S. market is expected to increase by 2%. $\Rightarrow m_{S,d,T} = .02$ All the other variables remain unchanged. $\Rightarrow y_{f,T} = y_{d,T} = m_{S,f,T} = 0$.

$$\Rightarrow s_{t,T} = .02$$

 $M_{S,d}$ increases 2% $\Rightarrow S_t$ increases 2% (depreciation of the USD).

<u>Note</u>: In more complicated monetary approach models, if investors also expect the U.S. Fed to quickly increase i_{US} to avoid inflationary pressures, the USD may appreciate instead of depreciate. ¶

• Monetary Approach: Sticky Prices

There are many variations of the monetary model.

• Popular variation: PPP is not a good short-run theory. We see *sticky prices* (in the short-run).

The sticky prices monetary model incorporates the fact that exchange rates, S_t , are more volatile than domestic prices of goods and services, P_d .

• Short-run reaction to a "shocks" -- say, a monetary shock

- Nominal prices (P_d) do not react instantaneously.
- Financial prices do. Then, S_t overreacts (depreciates more than it should in a PPP world) to bring $P_d & Q$ immediately to equilibrium.

• In the long-run, P_d adjusts and S_t appreciates accordingly. The short-run behavior for S_t is called *overshooting*.

This is a popular model to explain the movement of S_t after financial crisis.



(3) Portfolio-Balance Approach

It is also part of the Asset Approach of FX determination. Under this approach, the financial assets to be considered by investors are:

- Money: DC & FC
- Bonds: Domestic (DC-denominated) & Foreign (FC-denominated).

Investors' asset preferences may be similar across countries (*uniform* preference model), or investors may prefer assets of their home country (preferred local habitat model).

• S_t is determined to bring equilibrium to the investors' portfolios.

• The balance between DC bonds & FC bonds in a portfolio is positively related to expected excess return on DC bonds over FC bonds.

Example: An **increase** in the supply of DC-denominated bonds or i_f depreciates the DC.

• Structural Models: Evidence

Standard tests of structural models are based on a regression:

 $s_t = \alpha + \beta Z_t + \varepsilon_t$

where Z_t represents a *structural* explanatory variable: money growth, income growth rates, $(i_d - i_f)$, current accounts, supply of bonds, etc.

Usual results:

- Null hypothesis: H_0 : $\beta = 0$, is difficult to reject.

– The R^2 tends to be small.

• Many economists say: Structural models are misspecified, because of *structural change*: The model's parameters change with changes in economic policy!

For example, a new Chairman of the Fed may have an effect on the coefficient β . Then, S_t may become more sensitive to $(i_d - i_f)$.

Structural Models: Evidence
Event studies analyzing the movement of St around news announcements have found some support for structural model.
These event studies find that news about:

Greater than expected U.S. CA deficits ⇒ St ↑ (BOP approach).
Unexpected U.S. economic growth ⇒ St ↓ (Monetary approach).
Positive MS surprises ⇒ St ↓ (Monetary approach, if Fed is expected to quickly id ↑).
Unexpected increase of (id - if) ⇒ St ↑ (Monetary approach, sign of MS↑)

Regression-based structural models do poorly. But, the variables used in structural models tend to have power to explain changes in St.







<u>Martingale-Random Walk Model: Implications</u> The Random Walk Model (RWM) implies: E_t[S_{t+T}] = S_t.
Powerful theory: At time t, all the info about S_{t+T} is summarized by S_t.
<u>Theoretical Justification</u>: Efficient Markets (all available info is incorporated into today's S_t.)
Example: Forecasting with RWM
S_t = 1.60 USD/GBP
E_t[S_{t+7-day}] = 1.60 USD/GBP
E_t[S_{t+180-day}] = 1.60 USD/GBP
E_t[S_{t+10-year}] = 1.60 USD/GBP. ¶
<u>Note</u>: If S_t follows a RW, a firm should spend no resources to forecast S_{t+T}. • Martingale-Random Walk Model: Evidence

Meese and Rogoff (1983, *Journal of International Economics*) tested the shortrun forecasting performance of different models for the four most traded FX rates. They considered economic models (PPP, IFE, Monetary Approach, etc.) and the RWM.

The metric used in the comparison: MSE (mean squared error)

$$\Rightarrow \text{MSE} = \frac{\sum_{t=1}^{Q} \varepsilon_{t+T}^2}{Q} = \frac{\sum_{t=1}^{Q} (S_{t+T} - S_{t+T}^F)}{Q}$$

where $\varepsilon_{t+T} = S_{t+T} - S_{t+T}^{F}$ = forecasting error at horizon *T*.

 \Rightarrow The **RWM** performed *as well as* any other model. Big surprise!

Cheung, Chinn & Pascual (2005) checked M&R's results with 20 more years of data. \Rightarrow **RWM** still the **best model** in the **short-run**.

M&R started a big literature. In general, M&R's results hold in the shortrun (say, up to 6-months), but for longer horizons (say, 1-4 years), models can do better (PPP, IFE and Taylor rule models, individually or combined).

Example: MSE - Forecasting S_t (USD/GBP) with Forwards and the RWM Data: interest rate differential (in %) and S_t from 2014:II on. Using IRP, you calculate the forward rate, $F_{t,90}$, and, then, to forecast $E_t[S_{t+90}] = S_{t+90}^F$.

Using the RWM you forecast $E_t[S_{t+90}] = S_t$. Then, to check the accuracy of the forecasts, you calculate the MSE.

Quarter $(i_{US} - i_{UK})$		St	Forwa	rd Rate	Random Walk		
	00 010		$S_{t+90}^{F} = F_{t,90}$	$\varepsilon_{\text{t-FR}} = S_{\text{t}} - S_{t}^{F}$	$S_{t+90}^F = S_t$	$\varepsilon_{t-RW} = S_t - S_t^F$	
2014:II	-0.304	1.6883					
2014:III	-0.395	1.6889	1.6870	0.0019	1.6883	0.0006	
2014:IV	-0.350	1.5999	1.6872	-0.0873	1.6889	-0.0890	
2015:I	-0.312	1.5026	1.5985	-0.0959	1.5999	-0.0973	
2015:II	-0.415	1.5328	1.5014	0.0314	1.5026	0.0302	
2015:III	-0.495	1.5634	1.5312	0.0322	1.5328	0.0306	
2015:IV		1.5445	1.5615	-0.0170	1.5634	-0.0189	
MSE				0.04427		0.04443	
both MSEs are similar though the E 's MSE is a hit smaller (4% lower)							
our model are similar, mough the $\Gamma_{t,T}$'s model is a bit smaller (.470 lower).							

• Martingale-Random Walk Model: Empirical Models Trying to Compete Models of FX rates determination based on fundamentals not very good at explaining (& forecasting) S_t , especially in the short-run.

Many empirical models developed to better explain *equilibrium exchange rates* (EERs).

Some models are built to explain the medium- or long-run behavior of S_t , others are built to beat the forecasting performance of the RWM.

A short list of the new models includes CHEERs, ITMEERs, BEERs, PEERs, FEERs, APEERs, PEERs, and NATREX.

	UIP	PPP	Balassa- Samuelson	Monetary Models	CHEERs	ITMEERs	BEERs
Name	Uncovered Interest Parity	Purchasing Power Parity	Balassa- Samuelson	Monetary and Portfolio balance models	Capital Enhanced Equilibrium Exchange Rates	Intermediate Term Model Based Equilibrium Exchange Rates	Behavioural Equilibrium Exchange Rates
Theoretical Assumptions	The expected change in the exchange rate determined by interest differentials	Constant Equilibrium Exchange Rate	PPP for tradable goods. Productivity differentials between traded and nontraded goods	PPP in long run (or short run) plus demand for money.	PPP plus nominal UIP without risk premia	Nominal UIP including a risk premia plus expected future movements in real exchange rates determined by fundamentals	Real UIP with a risk premia and/or expected future movements in real exchange rates determined by fundamentals
Relevant Time Horizon	Short run	Long run	Long run	Short run	Short run (forecast)	Short run (forecast)	Short run (also forecast)
Statistical Assumptions	Stationarity (of change)	Stationary	Non- stationary	Non- stationary	Stationary, with emphasis on speed of convergence	None	Non- stationary
Dependent Variable	Expected change in the real or nominal	Real or nominal	Real	Nominal	Nominal	Future change in the Nominal	Real
Estimation Method	Direct	Test for stationarity	Direct	Direct	Direct	Direct	Direct

FEERs	DEERs	APEERs	PEERs	NATREX	SVARs	DSGE
Fundamental Equilibrium Exchange Rates	Desired Equilibrium Exchange Rates	Atheoretical Permanent Equilibrium Exchange Rates	Permanent Equilibrium Exchange Rates	Natural Real Exchange Rates	Structural Vector Auto Regression	Dynamic Stochastic General Equilibrium models
Real exchange rate compatible with both internal and external balance. Flow not full stock equilibrium	As with FEERs, but the definition of external balance based on optimal policy	None	As BEERs	As with FEERs, but with the assumption of portfolio balance (so domestic real interest rate is equal to the world rate).	Real exchange rate affected by supply and demand (but not nominal) shocks in the long run	Models designed to explore movements in real and/or nominal exchange rates in response to shocks.
Medium run	Medium Run	Medium / Long run	Medium / Long run	Long run	Short (and long) run	Short and long run
Non- stationary	Non- stationary	Non- stationary (extract permanent component)	Non- stationary (extract permanent component)	Non- stationary	As with theoretical	As with theoretical
Real Effective	Real Effective	Real	Real	Real	Change in the Real	Change relative to long rum steady state
Underlying Balance	Underlying Balance	Direct	Direct	Direct	Direct	Simulation

• Recent Models

• Overall, a negative message for short-time forecasters. The RWM does very well in the short-run, especially, 1-3 months.

• Recent literature focuses on building factor models for S_t , similar to the factor models used for equity & bond markets. For example, Verdelhan (2018) presents the following model for FC *j*:

$$s_{j,t+1} = \alpha_j + \beta_j \text{ Dollar}_{t+1} + \tau_i (i_{j,t} - i_t) + \delta_j \text{ Carry}_{t+1} + \gamma_j (i_{j,t} - i_t) * \text{ Carry}_{t+1} + \varepsilon_{j,t+1}$$

with the following factors:

Dollar: Average change in the value of FCs. Plays the role of the "Market."

Interest rate differential: Return from lending at i_i & borrowing at i_i (USD).

Carry: Average change in FX rates of high- vs low-interest rate FCs.

Conditional factor: Interaction term: $(i_{j,t} - i_t) * Carry_{t+1}$

• Factors:

• **Dollar:** Average change in the value of foreign currencies, in terms of USD.

$$Dollar_{t+1} = \frac{1}{N} \sum_{j} s_{j,t+1}$$

• Interest rate differential: Return from investing at foreign interest rate & borrowing at USD interest rate. In equilibrium, using IRP:

$$f_{j,t} - s_{j,t} \approx i_{j,t} - i_t$$

• **Carry factor:** Average change in FX rates of high-interest rate (*H*) versus FX rates of low-interest rate (*L*) currencies.

$$Carry_{t+1} = \frac{1}{N_H} \sum_{j \in H} S_{j,t+1} - \frac{1}{N_L} \sum_{i \in L} S_{j,t+1}$$

• **Conditional factor:** Interaction term: $(i_{j,t} - i_t) * Carry_{t+1}$

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**
- \diamond 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: $E_t[S_{t+T}] \implies Expectation of S_{t+T}$ taken at time t ("today"). • Easier to predict changes $\implies E_t[S_{t+T}]$. Note: From $E_t[S_{t+T}]$, we get $E_t[S_{t+T}] \implies E_t[S_{t+T}] = S_t * (1+E_t[S_{t+T}])$ • Based on a model for S_t , we generate $E_t[S_{t+T}]$: $S_t = f(X_t) \implies E_t[S_{t+T}] = E_t[f(X_{t+T})]$ 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. \implies We'll use Z_t to forecast the future S_{t+T} : $E_t[S_{t+T}] = g(Z_t)$

Example: What is $g(Z_t)$? Using PPP, we forecast USD/GBP changes one period ahead (T=1): 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} $E_t[S_{t+1}] = S_t * [1 + s_{t+1}^F] = S_t * [1 + (I_{US,t+1} - I_{UK,t+1})]$ 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. $E_t[S_{t+1}] = g(Z_t)$ $-E_t[S_{t+1}] = g(I_{US,t}, I_{UK,t})$ $= S_t * [1 + \alpha_0^{US} + \alpha_1^{US} I_{US,t} - \alpha_0^{UK} - \alpha_1^{UK} I_{UK,t}]$



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



- Statistical characteristics of the data
- **Experience** of the forecaster
 - \Rightarrow Mixture of **art** and science.

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





Fundamental Forecasting: Usual Estimation Process

<u>Note</u>: 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* (*byper*)*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

<u>Remark</u>: 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*."





• Exar	Example (continuation): In-sample PPP forecasting									
$S_{1996:2}^{F}$ =	$S_{1996:2}^F = 1.5107 \text{ USD/GBP}.$									
2. Fored	2. Forecast evaluation (Forecast error: S ^F _{1996:2} - S _{1996:2})									
$\varepsilon_{1996:2} = S_{1996:2}^F - S_{1996:2} = 1.5107 - 1.5529 = -0.0422.$										
For the	whole	sample	:	1 1	i i					
	Date	CPI U.S.	CPI U.K.	In-Sample Forecast (S ^F _{t+1})	Actual (St)	Fore cast Error $\mathcal{E}_{t+1}=S^{F}_{t+1}-S_{t+1}$	•			
	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 : [($MSE: [(-0.0422)^2 + (-0.0471)^2 + + (-0.1259)^2]/6 = 0.017063278$									

Note: Not true forecasting: At time t, I_{t+1} is unknown. We need $E_t[I_t]$. **Example 1**: *Out-of-sample* Forecast: $E_t[S_{t+1}] = f(X_t)$ • Simple forecasting model: Naive forecast $(E_t[I_{t+1}] = I_t)$ $E_t[S_{t+1}] = S_{t+1}^F = (E_t[S_{t+1}]/S_t) - 1 \approx I_{d,t} - I_{f,t}$ Using the above information we can predict $S_{1996:3}$: **1. Forecast S^F**_{1996:3} $S_{1996:3}^F = I_{US,1996:2} - I_{UK,1996:2} = .00535 - .01553 = -0.01018.$ $S_{1996:3}^F = S_{1996:2} * [1 + S_{1996:3}^F] = 1.5529 * [1 + (-0.01018)] = 1.53709$ **2. Forecast Evaluation** $\varepsilon_{1996:3} = S_{1996:3}^F - S_{1996:3} = 1.53709 - 1.5653 = -0.028210.$

More sophisticated forecasts using models for I, survey data on expectations of I, etc.

Example 1A: AR(1) model for inflation, $I_{US,t+1} = \alpha_0^{US} + \alpha_1^{US} I_{US,t} + \varepsilon_{US,t+1}.$ $I_{UK,t+1} = \alpha_0^{UK} + \alpha_1^{UK} I_{UK,t} + \varepsilon_{UK,t+1}.$

Suppose we estimate both equations. The estimated coefficients (a's) are: $a_0^{US} = .0036$, $a_1^{US} = .64$, $a_0^{UK} = .0069$, & $a_1^{UK} = .43$.

 $\Rightarrow I_{US,1996:3}^{F} = .0036 + .64 * (.00535) = .007024$ $\Rightarrow I_{UK,1996:3}^{F} = .0069 + .43 * (.01553) = .013578.$ $s_{1996:3}^{F} = I_{US,1996:3}^{F} - I_{UK,1996:3}^{F} = .007024 - .013578 = -.00655.$ $s_{1996:3}^{F} = 1.5529 \text{ USD/GBP} * [1 + (-.00655)] = 1.5427 \text{ USD/GBP}.$ $\varepsilon_{1996:3} = S_{1996:3}^{F} - S_{1996:3} = 1.5427 - 1.5653 = -0.0226.$

Example 1A (c	ontinuation)	: Exchange Ra	te Foreca	ists				
US Excel Regression Results for US Inflation Forecasts $(I_{US t+1})$:								
SUMMARY OUTPUT				e eoger i				
Regression Sta	atistics							
Multiple R	0.629674							
R Square	0.396489 🗲	— How muc	h variabili	ty of Y _t is e	xplained by X _t			
Adjusted R Square	0.391583							
Standard Error	0.006811	t c	<i>t-stat</i> tests $H_0: a_i=0$					
Observations	125	1-5						
	*	$t_{al} = a_1 / \text{SE}($	$t_{al} = a_1 / \text{SE}(a_1) = 0.640707 / 0.071274 = 8.9893$					
ANOVA		L	,	/				
	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 (c	ontinuation)	: I _{UK,t+1} - UK	Regressio	n Results:	
SUMMARY OUTPUT					
Regression S	tatistics				
Multiple R	0.425407				
R Square	0.180971 +	I expl	ains 18 109	6 of the vari	iability of Luz
Adjusted R Square	0.174312	UK,t-1		o or the var	UK,t
Standard Error	0.011305				
Observations	125	t-stat is sig	gnificant at	the 5% leve	l (t >1.96)
		=> Lagged	Inflation ex	plains curre	ent Inflation
ANOVA				1	
	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: <i>Out-of-sample</i> Forecasting FX with an Ad-hoc Model Forecast monthly MYR/USD changes with the following model: $s_{MYR/USD,t} = a_0 + a_1 (I_{MYR} - I_{USD})_t + a_2 (y_{MYR} - y_{USD})_t + \mathcal{E}_t$ 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 MOVA $t_{al}=a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ ANOVA $t_{al}=a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ ANOVA $t_{al}=a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Another the state of									
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: SUMARY OUTPUT Regression Statistics Multiple R 0.092703 R Square 0.018594 Adjusted R Square 0.0087 Standard Error 0.051729 Observations 112 ANOVA $\frac{df}{SS} \frac{SS}{MS} \frac{F}{Significance F}}$ Regression 2 0.002528 0.001264 0.47242 0.624762 Residual 109 0.291666 0.002676 Total 111 0.294195	Example 2: Out	<i>t-of-sample</i> For	ecasting FX w	vith an Ad	-hoc Mod	lel			
$s_{MYR/USD,t} = a_0 + a_1 (I_{MYR} - I_{USD})_t + a_2 (y_{MYR} - y_{USD})_t + \mathcal{E}_t$ Excel Regression Results: SUMARY OUTPUT Regression Statistics Multiple R 0.092703 R Square 0.018594 Adjusted R Square -0.0087 Standard Error 0.051729 Observations 112 Move $t_{al} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ ANOVA 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	Forecast monthl	y MYR/USI	O changes with	the follo	wing mod	lel:			
Excel Regression Results:SUMMARY OUTPUTRegression StatisticsMultiple R0.092703Multiple R0.092703Regression Results:Xt explains 1.86% of the variability of stAdjusted R Square-0.0087Standard Error0.051729Observations112ANOVA $t-stat$ tests H_o : $\alpha_i = 0$ ANOVA $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 0.624762$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 0.624762$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 0.624762$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 0.624762$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 0.624762$ Anova $t_{\alpha l} = a_1/SE(a_1) = 0.215927/0.105824 = 0.624762$ Anova $t_{\alpha l} = a_1/SE(a_$	S _{MYR}	$a_0 + a_0 +$	$a_1 \left(\mathbf{I}_{\mathrm{MYR}} - \mathbf{I}_{\mathrm{USI}} \right)$	$(y_1)_t + a_2 (y_2)_t$	_{MYR} – y _{USI}	$(\varepsilon_{\rm D})_{\rm t} + \varepsilon_t$			
SUMMARY OUTPUT Regression Statistics Multiple R 0.092703 R. Square 0.018594 Xt explains 1.86% of the variability of st Adjusted R Square -0.0087 Standard Error 0.051729 $t-stat$ tests $H_o: a_i = 0$ Observations 112 $t_{al} = a_1 / SE(a_1) = 0.215927 / 0.105824 = 2.040435$ 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	Excel Regression	n Results:							
Regression Statistics Multiple R 0.092703 K. square 0.018594 Xt explains 1.86% of the variability of st Adjusted R Square -0.0087 Standard Error 0.051729 $t-stat$ tests $H_o: a_i = 0$ Observations 112 $t_{al} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ 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	SUMMARY OUTPUT								
Multiple R 0.092703 R. Square 0.018594 Xt explains 1.86% of the variability of st Adjusted R Square -0.0087 $t_{explains} 1.86\%$ of the variability of st Standard Error 0.051729 $t_{explains} 1.86\%$ of the variability of s_t Observations 112 $t_{explains} 1.86\%$ of the variability of s_t ANOVA $t_{al} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ ANOVA $t_{al} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ Regression 2 0.002528 0.001264 0.47242 0.624762 Residual 109 0.291666 0.002676 0.624762 Total 111 0.294195 0.002676	Regression Stat	istics							
R. Square 0.018594 Xt explains 1.86% of the variability of st Adjusted R Square -0.0087 Standard Error 0.051729 Observations 112 ANOVA $t-stat$ tests $H_o: a_i = 0$ df SS MOVA df Standard SS MOVA df SS MS F Significance F Regression 2 0.002528 0.001264 109 0.291666 0.002676 Total 111 0.294195	Multiple R	0.092703							
Adjusted R Square -0.0087 Standard Error 0.051729 Observations 112 ANOVA $t-stat$ tests $H_o: a_i = 0$ $t_{al} = a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ ANOVA df SS MS F Significance F Regression 2 0.002528 0.001264 109 0.291666 0.002676 Total 111 0.294195	R Souare	0.018594	X_expl	ains 1 86%	of the vari	ability of s			
Standard Error 0.051729 <i>t-stat</i> tests $H_o: \alpha_i = 0$ $a_{1/2} E(a_1) = 0.215927/0.105824 = 2.040435$ ANOVA <i>df SS MS F Significance F</i> Regression 2 0.002528 0.001264 0.47242 0.624762 Total 111 0.294195	Adjusted R Square	-0.0087	n _t onp		or the vari	aomity of b _t			
Interstate Colspan="2">Interstate Colspan="2" Colspan="2" Interstate C	Standard Error	0.051729	+	t stat tests $\mathbf{H} \cdot \mathbf{a} = 0$					
$t_{al}=a_1/SE(a_1) = 0.215927/0.105824 = 2.040435$ ANOVA df SS MS F Significance F Regression 2 0.002528 0.001264 Regression 2 0.002528 0.001264 Colspan="2">O.002528 0.001264 O.47242 0.624762 Total 111 0.294195 Colspan="2">Colspan="2">Colspan="2">Colspan="2">Colspan="2">Colspan="2">Colspan="2">Colspan="2">Colspan="2">Colspan="2">Colspan="2"	Observations	112	<i>ι-</i>	i -situt tests Π_0 . $u_i = 0$					
ANOVA df SS MS F Significance F Regression 2 0.002528 0.001264 0.47242 0.624762 Residual 109 0.291666 0.002676 0.47242 0.624762 Total 111 0.294195 0.002676 0.002676 0.002676		•	$t_{al} = a_1 / \text{SE}(a)$	$t_{al} = a_1 / \text{SE}(a_1) = 0.215927 / 0.105824 = 2.040435$					
df SS MS F Significance F Regression 2 0.002528 0.001264 0.47242 0.624762 Residual 109 0.291666 0.002676 0.47242 0.624762 Total 111 0.294195 0.294195 0.294195 0.294195	ANOVA			1,	/				
Regression 2 0.002528 0.001264 0.47242 0.624762 Residual 109 0.291666 0.002676		df	SS	MS	F	Significance F			
Residual 109 0.291666 0.002676 Total 111 0.294195	Regression	2	0.002528	0.001264	0.47242	0.624762			
Total 111 0.294195	Residual	109	0.291666	0.002676					
	Total	111	0.294195	/					
				/					
Coefficients Standard Error t Stat P-value		Coefficients	Standard Error	t Stat 🖌	P-value				
Intercept 0.006934 0.005175 1.339903 0.180277	Intercept	0.006934	0.005175	1.339903	0.180277				
Y Variable I (I I I) 0.215027 0.105924 2.040425 0.041207	X Variable 1 (I I)	0.215027	0 105934	2.040425	0.041207				
X variable $2 (y_{MYR} = 1050)_t$ 0.213727 0.105824 2.040435 0.041307 X Variable $2 (y_{MYR} = y_{MYR})$ 0.001592 0.051676 1.772428 0.076326	X Variable 2 $(v_{MYR} - v_{USD})_t$	0.215927	0.105824	2.040435	0.041307				

Example 2 (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: $t_{a1} = |2.040435| > 1.96$ (reject H_0); $t_{a2} = |1.772428| < 1.96$ (can't reject H_0) Do the signs make sense? $a_1 = .2159 > 0 \implies PPP$ $a_2 = .0915 > 0 \implies Trade Balance$ 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): $E_t[INF_{t+1}] = 3\% \& E_t[INC_{t+1}] = 2\%$. $E_t[s_{MYR/USD,t+1}] = .0069 + .2159 * (.03) + .09157 * (.02) = .0152$.

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

Example 2 (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 $S_t = 3.1021$ MYR/USD $S_{t+1}^F = 3.1021$ MYR/USD * (1 + .0152) = 3.1493 MYR/USD. 2. Forecast Evaluation Suppose $S_{t+1} = 3.0670$ MYR/USD. $\varepsilon_{t+1} = S_{t+1}^F - S_{t+1} = 3.1493 - 3.0670 = 0.0823.$ ¶

• 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.

• 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-month} = .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-month}.
Based on the FS forecast, Sternin buys CAD forward at F_{t,1-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.
(B) Suppose that S_{t+1-mo} = .7315 USD/CAD.
(B) Suppose that S_{t+1-mo} = .7315 USD/CAD.
(B) Suppose that S_{t+1-mo} = .7315 USD/CAD.
(A) Suppose that S_{t+1-mo} = .7315 USD/CAD.
(B) Suppose that S_{t+1-mo} = .7315 USD/CAD.

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.













• 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 outof-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, expost selection of trading rules, estimation of risk & transaction costs.



• Estimate the models using data up to **2019:III**. Evaluate *in-sample* results (t-stats & R^2).

• Forecast 2019:IV - 2022:IV. Evaluate out-of-sample results with MSE.

• Forecast 2019:IV - 2022:IV using RWM. Evaluate forecasts with MSE.

• For each currency, select the "best" model –i.e., lowest MSE. Forecast **2023:I**.

Class assignment
Ad-hoc Model: s_{t,T} = α + β₁ (I_{d,t} - I_{f,t}) + β₂ (i_{d,t} - i_{f,t}) + β₃ (y_{d,t} - y_{f,t}) + ε_t
Estimate Model for USD/GBP, using whole sample: 1978:II - 2020:III.

1) Do the signs make sense?
2) Evaluate model with t-stats and R².
3) a. Estimate model with data up 2021:III. (Estimation period: 1978:II - 2021:III.)
b. Generate forecasts for 2021:IV to 2022:IV.
4) Compute MAE for forecasts
5) Compute Forward Rates using IRP formula for 2021:IV to 2022:IV. Use forward rate as a forecast. Compute MAE.
6) Briefly discuss success/failure of model.