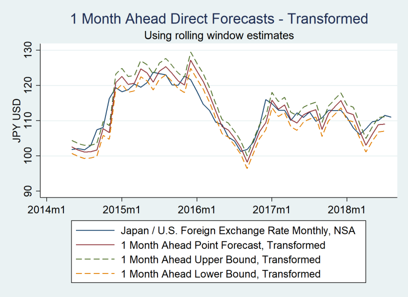

EC4304: Forecasting Exchange Rates

Anisah ARZ
Arya Ravi
Lim Fang Yi
Prerana Hiriyur

Overview

Introduction

The General Idea

- FX market is the **largest** financial market in the world (transaction volume $\approx$ US$5 trillion per day)
- Including market volatility, i.e. **VIX**
- Our case studies: JPYUSD & EURUSD

Economic theory + Macroeconomic Data

- Taylor, J. B. (1993). Discretion versus Policy Rules in Practice
- Ince, O., Molodtsova, T., & Papell, D. H. (2016). Taylor rule deviations and out-of-sample exchange rate predictability.

Random Walk

Meese & Rogoff (1983)

The paper tested the random walk against:

1. Flexible price (Frenkel-Bilson) monetary model
2. Sticky price (i.e. Dornbush-Frankel) monetary model
3. Hooper-Morton model

Ultimately, random walk had

- higher accuracy
- smaller forecast errors

Taylor's Rule Differentials

Anisah ARZ,
Arya Ravi,
Lim Fang Yi,
Prerana Hiriyur

From the original Taylor's Rule

$$i_t - i_t^* = \alpha + 1.5(\pi_t - \pi_t^*) + 0.5(y_t^g - y_t^{g^*})$$

Let $e_{t+1} =$ log of nominal exchange rate

Modified Taylor's Rule

$$\Delta e_{t+1} = e_{t+1} - e_t = \beta_0 + \beta_1 \pi_t + \beta_2 \pi_t^* + \beta_3 y_t^g + \beta_4 y_t^{g*} + \varepsilon_t$$

Taylor's Rule Differentials + VIX

Incorporating the VIX

VIX: Market volatility implied by 30 day S&P 500 call options

- Positive relationship between VIX and USD/G10 Volatility (Lequeux & Menon, 2010)
- Taylor's Rule does not fully capture the **short run** fluctuations in exchange rate

Final potential model equation

$$\Delta e_{t+1} = \beta_0 + \beta_1 \pi_t + \beta_2 \pi_t^* + \beta_3 y_t^g + \beta_4 y_t^{g*} + \Delta VIX_t + \varepsilon_t$$

Checking for Serial Autocorrelation

Ljung-Box Q Test

Model	Q-statistic	White Noise - Y/N?
Taylor's rule (TR)	0.001	N
TR + 1 lag of VIX	0.017	N
TR + 2 lags of VIX	0.018	N
TR + 3 lags of VIX	0.033	N

Implications

- Errors of all potential models are **serially correlated**
  - All further testing on potential models must take this into account

Granger Causality Test

We conducted the Granger Causality Test on the **individual** components of our model: *variables** in Taylor's rule fundamentals, and lags of VIX

Model	F-statistic	Granger causes - Y/N?
Taylor's rule	3.150	Y**
1 lag of VIX	5.090	Y**
2 lags of VIX	2.810	Y*
3 lags of VIX	1.910	N
Note:		*p<0.1; **p<0.05; ***p<0.01

Predictive Least Squares

PLS instead of AIC/BIC

- Dependent variable of random walk model versus other potential models are **different**, i.e. Δe_{t+1} vs. s_{t+1}
- Uncomparable using AIC/BIC

PLS results

Random Walk	TR	TR+1 lag of VIX	TR+2 lags of VIX
1.948	2.103	2.081	2.042

- Random walk has the lowest PLS, closely followed by TR + 2 lags of VIX model
  - Choose TR + 2 lags of VIX model?
  - Not yet

Forecast Combination

Granger-Ramanathan (GR)

Using GR forecast regression to compute **optimal weights** for the best forecast combination that minimises error

Reasons for choosing GR method

- **Biased** forecasts due to correlated error terms
- **Correlated** forecasts due to common Taylor's Rule variables
- Only requires forecasted values, no model specification

Granger-Ramanathan Forecast Regression

Begin with forecasts from all models

```
Constrained linear regression                    Number of obs     =         53
                                                 Root MSE          =     1.9076

 ( 1)  f_rw_jpy + trhat_exrate + vix1hat_exrate + vix2hat_exrate = 1
```

jpy_exrate~a	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
f_rw_jpy	.6683863	.2320901	2.88	0.006	.2019838	1.134789
trhat_exrate	$\boxed{-.5854611}$	.6788259	-0.86	0.393	-1.949613	.7786905
vix1hat_ex~e	$\boxed{-2.149703}$	1.639661	-1.31	0.196	-5.444725	1.145319
vix2hat_ex~e	3.066778	1.666938	1.84	0.072	-.2830586	6.416615
_cons	.1677078	.2650085	0.63	0.530	-.3648468	.7002623

After dropping forecasts with negative coefficients...

```
Constrained linear regression                    Number of obs     =         53
                                                 Root MSE          =     1.9252

 ( 1)  f_rw_jpy + vix2hat_exrate = 1
```

jpy_exrate~a	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
f_rw_jpy	.6219672	.226671	2.74	0.008	.1669062	1.077028
vix2hat_ex~e	.3780328	.226671	1.67	0.101	-.0770281	.8330938
_cons	.1847676	.2672215	0.69	0.492	-.3517019	.7212372

Out of Sample Forecasts

Components of OOS Forecast for JPYUSD

- **Model**: Taylor's Rule with 2 lags of VIX
- **Forecast horizon**: 1-month ahead, 6-month ahead and 12-month ahead forecasts from 2014m5 to 2018m8
- **Forecasted variable**: 1 period log differential of exchange rate (Δe_{t+1}) (later transformed)
- **Estimation window**: Rolling, with 157 observations

Out of Sample Forecasts

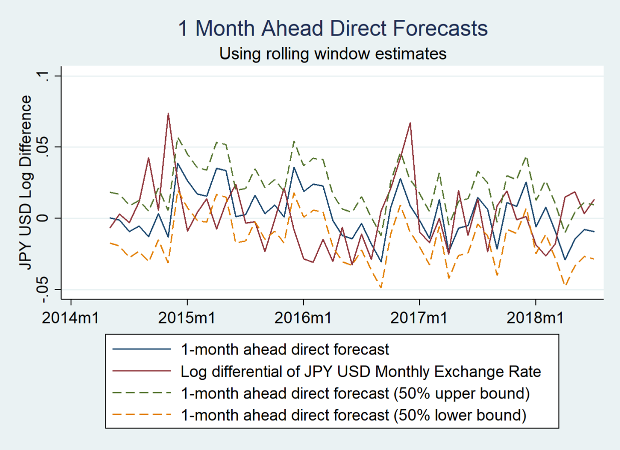

Figure: 1-month ahead direct forecasts of log differentials (Δe_{t+1})

Out of Sample Forecasts (transformed)

Using observed previous period values,

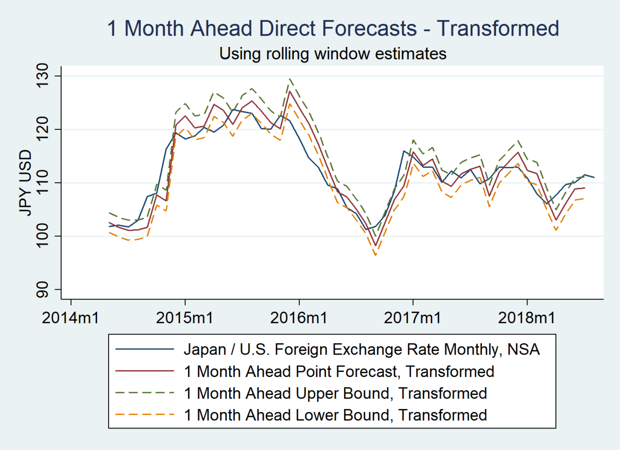

Figure: Transformed exchange rate forecasts

Mean Squared Errors

Reasons for using Mean Squared Errors

- Mean Error and Mean Absolute Error do not reflect error variance
- MSE is a more complete measure of forecast accuracy that incorporates both mean error and error variance.

Transformed forecasts

- Comparing forecasted and actual exchange rate, calculate squared loss and MSE
- Only comparing **1-month** ahead direct forecasts as uncertainty increases with forecast horizons.

Comparing MSE

Currency Pair	JPYUSD	EURUSD
Random Walk MSE	6.566	0.0002903
Chosen Model MSE	10.300	0.0003060
Difference	-3.734	-0.000157

Diebold Mariano Test

$$d_t = L(e^1_{t+h|h}) - L(e^2_{t+h|h})$$

Set Up

- First model: Random walk; Second model: Chosen model
- Negative difference means that random walk model has lower MSE and is thus more accurate

T-test

- Using robust errors
- Due to small POOS window, do the small sample correction

Diebold Mariano Test

Currency Pair	JPYUSD	EURUSD
Ljung-Box Q-Stat P-Value	0.4599	0.4239
DM test coeff.	-3.736	-0.0000157
Q-stat	0.012	0.363
Q-stat with sample-size correction	0.013	0.581
Is the difference significant?	Y	**N**

Interpretation

- JPYUSD: Random walk is conclusively **better** at predictive movements
- EURUSD: Random walk and chosen model are **not** significantly different in predictive power

Limitations

In the methodology

- Using Germany as a proxy $\longrightarrow$ good enough to model effects of Euro?
- Analysis with more currency pairs
- Frequency of data for forecasting

In the datasets

- Granger Causality tests performed on in-sample observations **may not hold** in OOS observations
- PLS is highly sensitive to number of observations used in estimating the forecast model, tends to **overestimate** MSFE and tends to be over-parsimonious

Conclusion

- Random walk is conclusively better than any Taylor Rule and Taylor Rule+VIX model in forecating movements of JPYUSD
- Results of DM test could not conclusively determine random walk to be significantly better our chosen Taylor Rule with 1 lag of VIX model
- Potential area for future study: Incorporating VIX into a forecasting model could beat the random walk model with other "safe-haven" currency pairs such as USDCHF and AUDJPY