Exchange Rate Volatility Forecasting

Using GARCH models in R

Roger Roth
Martin Kammlander
Markus Mayer

universität wien

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Agenda

Importance of ER Forecasting

- Breakdown of the *Bretton Woods* system sharply increased the relevance of ER forecasting.
- Examples for the necessity of ER forecasts:
  - Hedging transaction exposure
  - Long-term portfolio investments
  - Foreign direct investments
  - Uncovered interest arbitrage

Predictability of the Conditional Mean I

- An optimal forecast always contains a conditonal mean forecast.
- Large deviations like they occur in ER crisis (i.e. Asian crisis) cannot be forecasted. Every conventional forecasting model is working within the parameters of the Gaussian.
- The *random walk* dominates all monetary models, at least in the short run. This core statement of Meese and Rogoff (1983) is seen as one of the most empirically evident findings in macroeconomics.
- Even central bank interventions do not have a significant effect on the ERs, because the interventions are quite small compared to foreign exchange activity.

Predictability of the Conditional Mean II

- Illustration of random walk forecast: if we have an ER of 1.3 today, we forecast an ER of 1.3 for next quarter.
- But according to Vitek (2005), there exists evidence of long term predictability. As we can survey the scientific debate, most but by far not all economists agree.

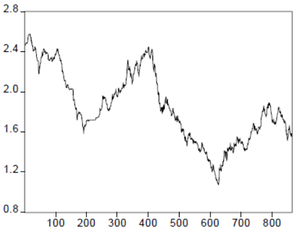
Predicability of the Volatility I

- The *volatiltiy* is measured by the conditional variance of the forecast.
- Even if it is not possible to forecast the mean, the forecast of the volatility is still of importance. Uncertainty regarding the value of goods and securities create risk. Even firms which are willing to take risk, prefer to take risk in their core market. Studies found that they majority of firms are risk averse to ER fluctuations. They want to hedge against these risks.

Modelling ER I

- Observation of *heteroscedasticity* is common among economic time series, which are determined in financial markets.
- Foreign exchange rates exhibits variations in the volatility over time. *Volatility clustering* (see figure) is key feature of financial time series.

Modelling ER II



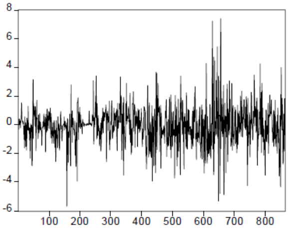


Figure: Level and first differences of a typical exchange rate

- The standard framework for dealing with volatility are the ARCH/GARCH models.

Modelling ER III

- Hsieh (1989) shows that different specifications of ARCH/GARCH models usually describe different currencies better than a unique model. For instance, some currencies show a higher degree of seasonality than others due to a higher amount of exports of goods around christmas.
- In the further analysis we make use of a GARCH(1,1) model (Bollerslev, 1986).
- In this model the variance is is not just dependent on the series itself, but also on itself.

Definition

The GARCH(1,1) model is described by
(1) Mean Equation: $Y_t = X_t'\theta + \epsilon_t$
(2) Variance Equation: $\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$

Modelling ER IV

- Advantages of choosing a GARCH(1,1) model:
  - They are more *parsimonious* than ARCH models. Therefore we avoid overfitting
  - Most common specification of ARCH/GARCH family.
  - They fit financial data well, if they are observed with high frequency.

Different Forecasting Techniques I

- Commercial ER forecasting has flourished since the 1980s, but it is regarded with great scepticism by the scientific community.
- Structural models which were developed in the last decades were not able to outperform the random walk.
- Forecasting techniques used in practice can be categorized after Moosa (2001) into
  - Univariate time series methods (GARCH etc.)
  - Multivariate time series methods
  - Market based forecasting using spot and forward ER.
  - Fundamental approach (usually based on economic equilibrium models and the variables, which are employed like GNP, consumption, trade balance, inflation, interest rates, unemployment rate etc.)

Different Forecasting Techniques II

- Judgemental and composite ER forecasts
- Technical analysis looks for the repetitition of specific patterns(trendlines etc). Not science!
- Recent developments include chaos theory & Artificial Neural Networks (ANNs)

Evaluating Commercial Forecasts Accuracy

- The prediction accuracy of exchange rate volatility forecasts is most commonly tested by mean-squared-error (MSE), mean absolute forecast error (MAE) & R-squared
- Levich (1979) compared commercial forecasts with the *forward rate* as a benchmark. He interpreted the forward rate as a for everybody available and free forecast. He found, that 70% of the commercial forecasts were less accurate than the forward rate.

Non-Academic Forecasting in Practice

Description of Data

- We analyse a *floating* ER system on a time scale which probably is large enough to contain also exogenous shocks.
- YEN/USD ranging from 1971-2009 on a daily basis (high frequency data).

Returns of the ER

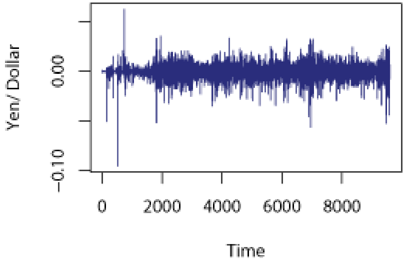


Figure: Returns of the ER

Testing of the normality assumption

We test if the normality assumption is justified for our data. Therefore we plot the sample quantiles against the theoretical quantiles.

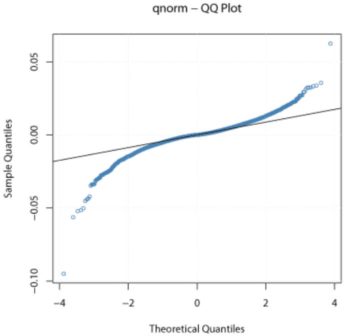


Figure: QQ-Plot of the sample quantiles against the theoretical quantiles

Implementation in R

- Is the use of an ARCH/GARCH model justified? We run the ARCH LM-Test in R.

```
> ArchTest (dlexr, lags=30, demean = FALSE)

        ARCH LM-test; Null hypothesis: no ARCH effects

data:  dlexr
Chi-squared = 298.2216, df = 30, p-value < 2.2e-16
```

Figure: Syntax and output for testing for ARCH effects using the FinTS package

Testing for ARCH Effects

The sample ACF of the percentage changes shows small serial correlation for lag 9 and 10

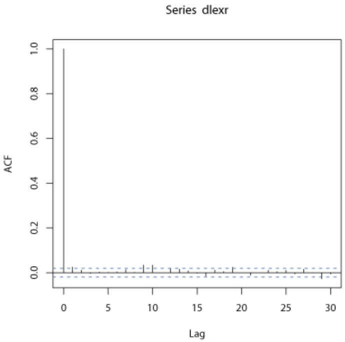


Figure: Sample ACF of the percentage change

Testing for ARCH Effects

The ACF of the squared percentage changes dies out slowly, indicating the possibility of a variance process close to being non-stationary.

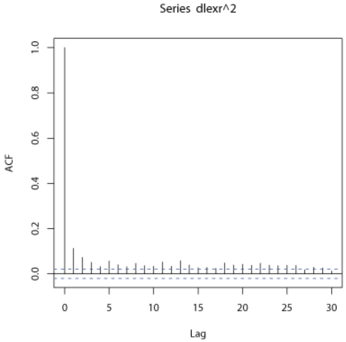


Figure: The ACF of the squared percentage changes

Testing for ARCH Effects

The PACF of squared percentage changes shows large spikes at the beginning suggesting that the percentage changes are not independent and have some ARCH effects.

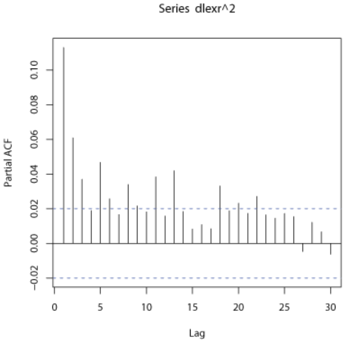


Figure: Sample PACF of squared percentage changes

Forecasting Output

Forecasting Output for 150 periods.

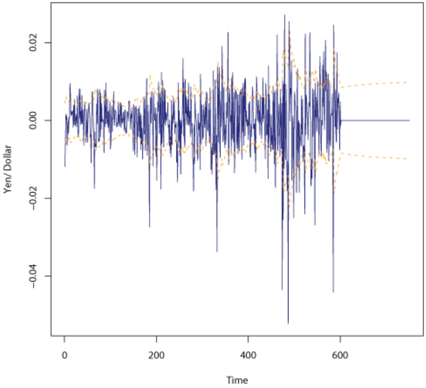
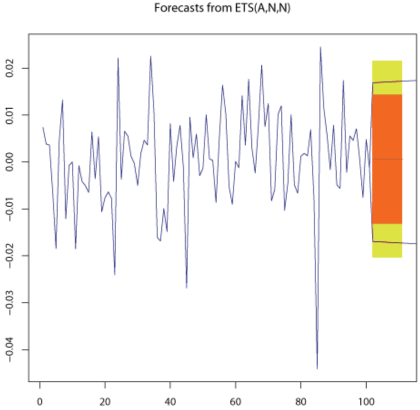


Figure: Forecasting output using the FGARCH package inR

Forecasting Output

Compariso of forecasting output of exponential smoothing, with 80% KI (orange) and 95% (yellow) and GARCH(1,1) 95% (blue lines).



Thank you for your attention!

John Kenneth Galbraith:

> *"There are two forecasters, those who don't know and those who don't know that they don't know."*

The coefficients for the conditional variance equation are highly significant.

```
> summary(dlexr.g2)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 1), data = dlexr)

Mean and Variance Equation:
 ~arma(0, 0) + ~garch(1, 1)

Conditional Distribution:
 dnorm

Coefficient(s):
          mu         omega        alpha1         beta1
-2.47366e-05   1.17845e-06   1.36039e-01   8.52219e-01

Error Analysis:
         Estimate  Std. Error  t value Pr(>|t|)
mu     -2.474e-05   5.236e-05   -0.472    0.637
omega   1.178e-06   9.648e-08   12.214   <2e-16 ***
alpha1  1.360e-01   8.405e-03   16.185   <2e-16 ***
beta1   8.522e-01   7.803e-03  109.223   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 -35602.06    normalized:  -3.708548

Standadized Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  130980.7  0
 Shapiro-Wilk Test  R    W      NA        NA
 Ljung-Box Test     R    Q(10)  43.48708  4.068515e-06
 Ljung-Box Test     R    Q(15)  51.85641  5.965716e-06
 Ljung-Box Test     R    Q(20)  55.2348   3.787172e-05
 Ljung-Box Test     R^2  Q(10)  9.258259  0.5077819
 Ljung-Box Test     R^2  Q(15)  10.74356  0.7705524
 Ljung-Box Test     R^2  Q(20)  11.62238  0.9284606
 LM Arch Test       R    TR^2   9.971807  0.6184341

Information Criterion Statistics:
     AIC      BIC      SIC     HQIC
7.417930 7.420917 7.417929 7.418943

Description:
 Mon Jun 08 12:43:54 2009 by user: Pclabor
```

Figure: Output of the GARCH fit summary