Exchange Rate Regime Classification with Structural Change Methods

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Overview

- Exchange rate regimes
- What is the new Chinese exchange rate regime?
- Frankel-Wei regression for de facto exchange rate regime classification
- Regime stability
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  - Monitoring
  - Dating
- Applications: Indian exchange rate regimes
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Exchange rate regimes

The foreign exchange (FX) rate regime of a country determines how it manages its currency wrt foreign currencies. It can be

- *floating:* currency is allowed to fluctuate according to the foreign exchange market,
- *pegged:* currency is fluctuating only in a certain band, pegged to (basket of) other currencies,
- *fixed:* direct convertibility to another currency.

Problem: The *de facto* and *de jure* FX regime in operation in a country often differ.

$\Rightarrow$ Interest in methods for data-driven classification of FX regimes (see e.g., Reinhart and Rogoff, 2003).

Chinese exchange rate regime

China gave up on a fixed exchange rate to the US dollar (USD) on 2005-07-21.

The People's Bank of China announced that the Chinese yuan (CNY) would no longer be pegged to the USD but to a basket of currencies with greater flexibility.

This generated a lot of interest, both in the media and the scientific literature. However, little support could be found for the announcements of the People's Bank of China.

Shah, Zeileis, Patnaik (2005) investigate the Chinese *de facto* FX regime based on the so-called *Frankel-Wei regression model* using structural change methods.

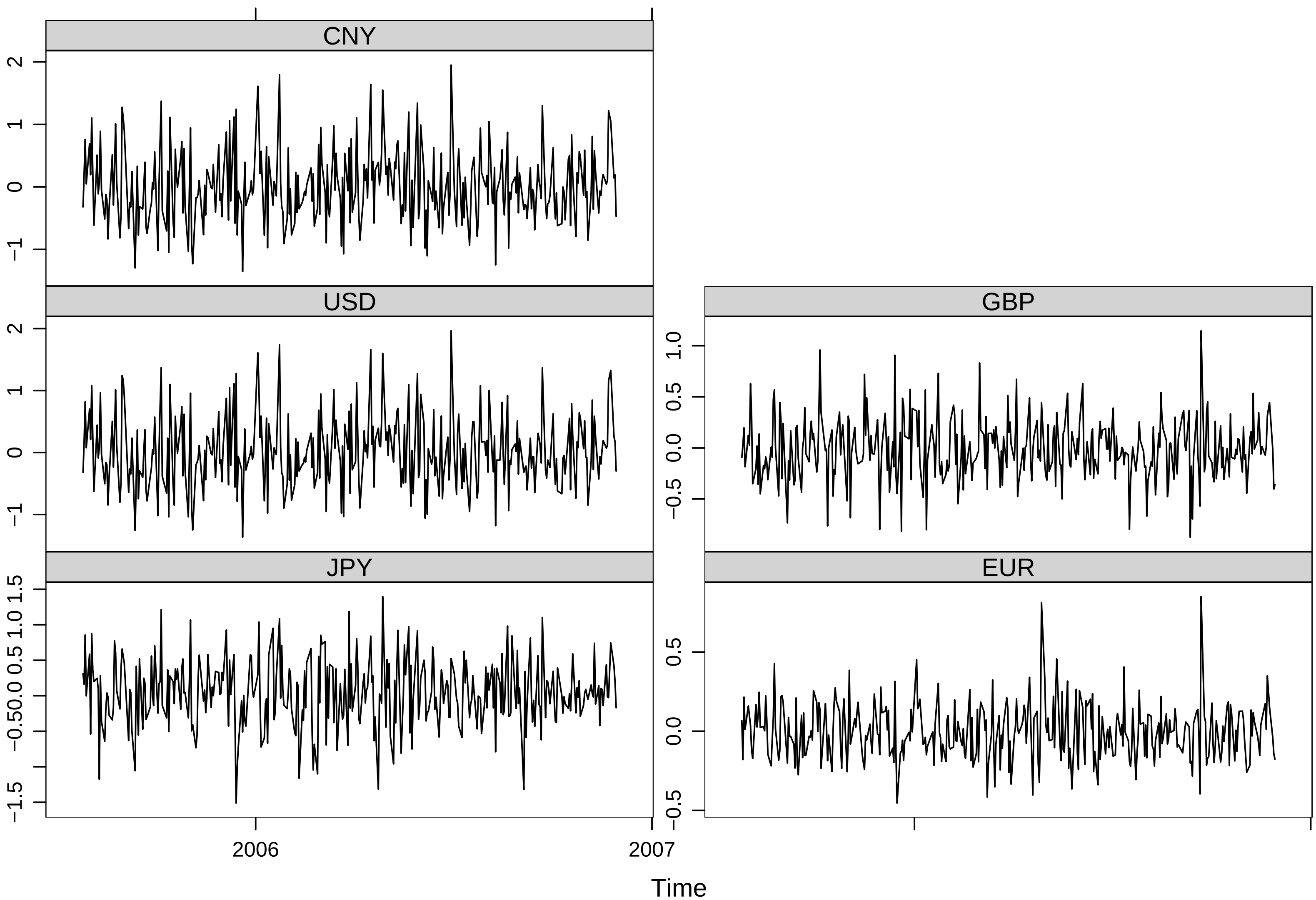
Frankel-Wei regression

The Frankel-Wei model (Haldane and Hall 1991, Frankel and Wei 1994) is the popular workhorse for de facto FX regime classification. It is a linear regression based on log-returns of cross-currency exchange rates (with respect to some floating reference currency).

Fitting the model for CNY with regressors USD, JPY, EUR and GBP (all wrt CHF) based on data up to 2005-10-31 ($n = 68$) shows that a plain USD peg is still in operation:

$$\begin{aligned} \mathrm{CNY}_i &= -0.005 + 0.9997\,\mathrm{USD}_i + 0.005\,\mathrm{JPY}_i \\ &\quad -0.014\,\mathrm{EUR}_i - 0.008\,\mathrm{GBP}_i + \hat{u}_i. \end{aligned}$$

Frankel-Wei regression



Frankel-Wei regression

```
Call:
fxlm(formula = CNY ~ USD + JPY + EUR + GBP, data = window(cny,
    end = as.Date("2005-10-31")))

Residuals:
      Min        1Q    Median        3Q       Max
-0.065697 -0.021036  0.001147  0.021440  0.069985

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.004782   0.003688  -1.297    0.199
USD          0.999653   0.008779 113.868   <2e-16 ***
JPY          0.004668   0.010669   0.437    0.663
EUR         -0.014238   0.026516  -0.537    0.593
GBP         -0.007744   0.014568  -0.532    0.597
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02953 on 63 degrees of freedom
Multiple R-Squared: 0.9979,        Adjusted R-squared: 0.9978
F-statistic:  7577 on 4 and 63 DF,  p-value: < 2.2e-16
```

Regime stability

Questions:

1. Is this model for the period 2005-07-26 to 2005-10-31 stable or is there evidence that China kept changing its FX regime after 2005-07-26? (*testing*)

2. Depending on the answer to the first question:

   - Does the CNY stay pegged to the USD in the future (starting form November 2005? (*monitoring*)
   - When and how did the Chinese FX regime change? (*dating*)

Regime stability

In practice: Rolling regressions are often used to answer these questions by tracking the evolution of the FX regime in operation.

More formally: Structural change techniques can be adapted to the Frankel-Wei regression to estimate and test the stability of FX regimes.

Problem: Unlike many other linear regression models, the stability of the error variance (fluctuation band) is of interest as well.

Solution: Employ an (approximately) normal regression estimated by ML where the variance is a full model parameter.

Regime stability

The Frankel-Wei regression is essentially a standard linear regression model

$$y_i \quad = \quad x_i^\top \beta \; + \; u_i$$

with coefficients β and error variance σ^2.

The corresponding estimating functions for the parameters are

$$\begin{aligned} \psi_\beta(y, x, \beta) \; &= \; (y - x^\top \beta)\, x, \\ \psi_{\sigma^2}(y, x, \beta, \sigma^2) \; &= \; (y - x^\top \beta)^2 - \sigma^2. \end{aligned}$$

To test the stability of the parameters β and σ^2, it can be assessed whether the empirical estimating functions $\widehat{\psi}_i$ differ systematically from their zero mean.

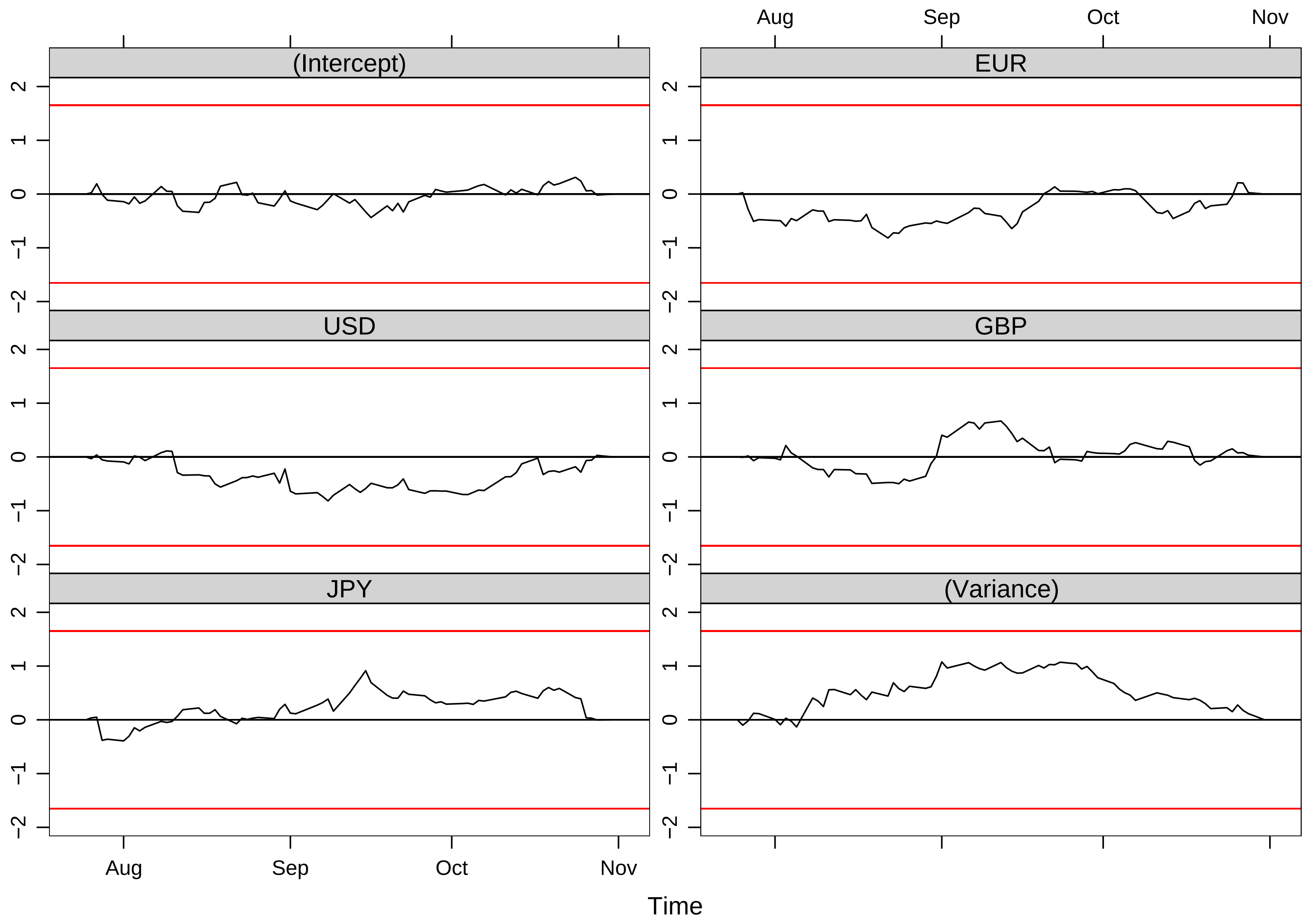
Testing

To capture systematic deviations the empirical fluctuation process of scaled cumulative sums of empirical estimating functions is computed:

$$efp(t) \quad = \quad \hat{B}^{-1/2}\, n^{-1/2} \sum_{i=1}^{\lfloor nt \rfloor} \hat{\psi}_i \qquad (0 \le t \le 1).$$

- theoretical limiting process is the Brownian bridge (FCLT),
- choose boundaries which are crossed by the limiting process (or some functional of it) only with a known probability α.
- if the empirical fluctuation process crosses the theoretical boundaries the fluctuation is improbably large $\Rightarrow$ reject the null hypothesis.

Testing



(Intercept)
EUR
USD
GBP
JPY
(Variance)
Aug
Sep
Oct
Nov
2
1
0
−1
−2
Time

Testing

This corresponds to using a double maximum statistic

$$\max_{j=1,\dots,k} \max_{i=1,\dots,n} |efp_j(i/n)|$$

which is 1.078 for the CNY regression ($p = 0.73$).

Other test statistics that could be used include

- Nyblom-Hansen test using a Cramér-von Mises functional,
- Andrews' sup*LM* test,

which also fall into this framework of fluctuation tests (Zeileis, 2005).

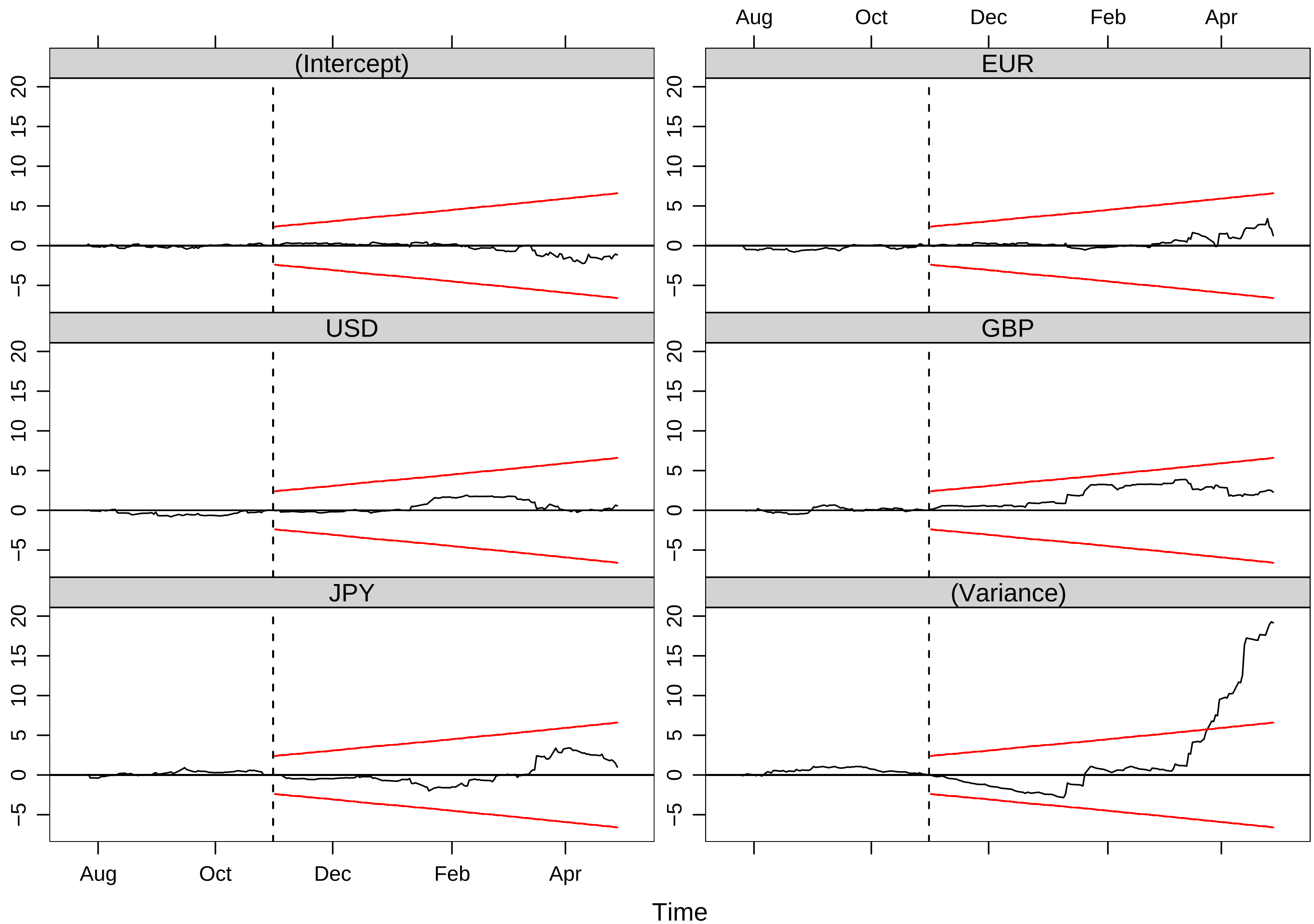
Montoring

The same ideas can be used to test whether incoming observations $i > n$ conform with an established model.

Basic assumption: The model parameters are stable in the history period $i = 1, \dots, n$.

The same empirical fluctuation process $efp(t)$ is updated in the monitoring period and suitable boundaries can again be derived (Zeileis *et al.*, 2005, Zeileis, 2005).

Montoring



(Intercept)
EUR
USD
GBP
JPY
(Variance)
Aug
Oct
Dec
Feb
Apr
Time
−5
0
5
10
15
20

Montoring

This signals a clear increase in the error variance which is picked up by the monitoring procedure on 2006-03-27.

However, all other regression coefficients did not change significantly, signalling that a USD peg is still in operation.

Using data from the extended period up to 2006-12-01, we fit a segmented model to determine where and how the model parameters changed.

Dating

Bai and Perron (2003) describe a strategy for estimating the breakpoints in a linear regression based on the residual sum of squares (RSS).

For the additive objective function RSS, a dynamic programming algorithm that evaluates all potential m-partitions (i.e., with m breakpoints) is available. It is an application of Bellman's principle of optimality.

Problem: Dating based on the RSS does not exploit changes in the error variance (only regression coefficients).

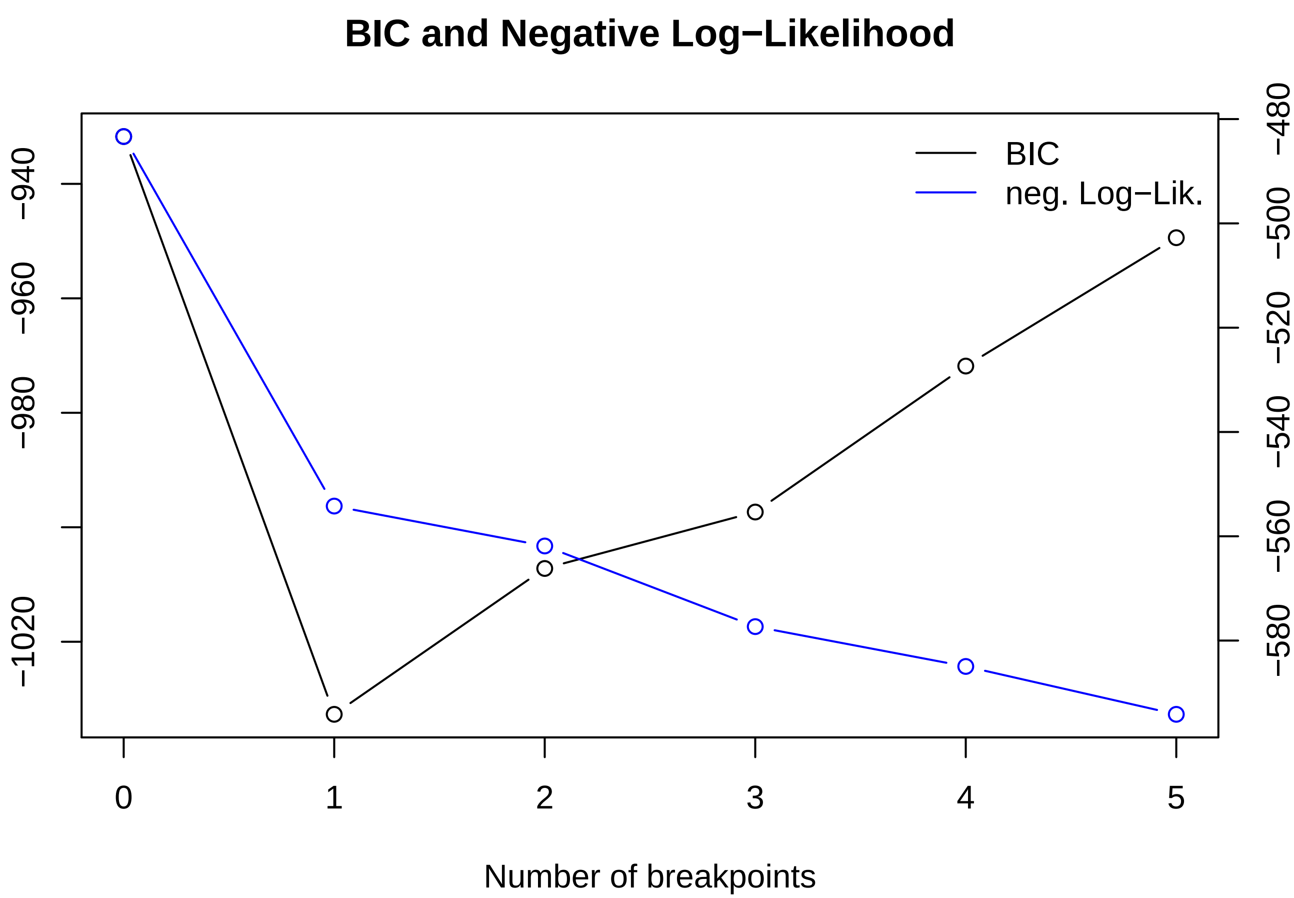
Dating

For the Frankel-Wei regression, we employ the same dynamic programming algorithm based on a different additive objective function: the (negative) log-likelihood from a normal model $\Rightarrow$ changes in the variance are also captured.

For a fixed given number of breaks m, the optimal breaks (wrt log-likelihood) can be found. To determine the number of breaks, standard techniques for model selection can be applied here, e.g., information criteria or sequential tests.

Often, these do not work well out of the box, but should be handled with care and enhanced by other techniques.

Dating


BIC and Negative Log−Likelihood
BIC
neg. Log−Lik.
−940
−960
−980
−1020
−480
−500
−520
−540
−560
−580
0
1
2
3
4
5
Number of breakpoints

Dating

The estimated breakpoint (maximizing the segmented likelihood) is 2006-03-14.

The corresponding parameter estimates are

	(Intercept)	USD	JPY	EUR	GBP	(Std. Error)
2005-07-26--2006-03-14	-0.005	0.999	0.005	-0.015	0.007	0.028
2006-03-15--2006-11-29	-0.016	0.993	0.009	-0.009	-0.025	0.074

and correspond to a

- very tight USD peg,
- slightly relaxed USD peg.

Indian FX regimes

To show how this methodology can be employed in practice, the evolution of the Indian FX regime starting from 1993-04-01 is analyzed.

All functionality is available within the R system for statistical computing using the **strucchange** package and a set of convenience interfaces in the package **fxregime**.

```
R> library("fxregime")
R> data("FXRatesCHF", package = "fxregime")
R> inr <- fxreturns("INR", frequency = "weekly",
+     data = window(FXRatesCHF,
+         start = as.Date("1993-04-01")))
```

Indian FX regimes

A simple convenience interface to `lm()` is used for fitting the regression for the full sample period (1993-04-01 to 2006-12-01):

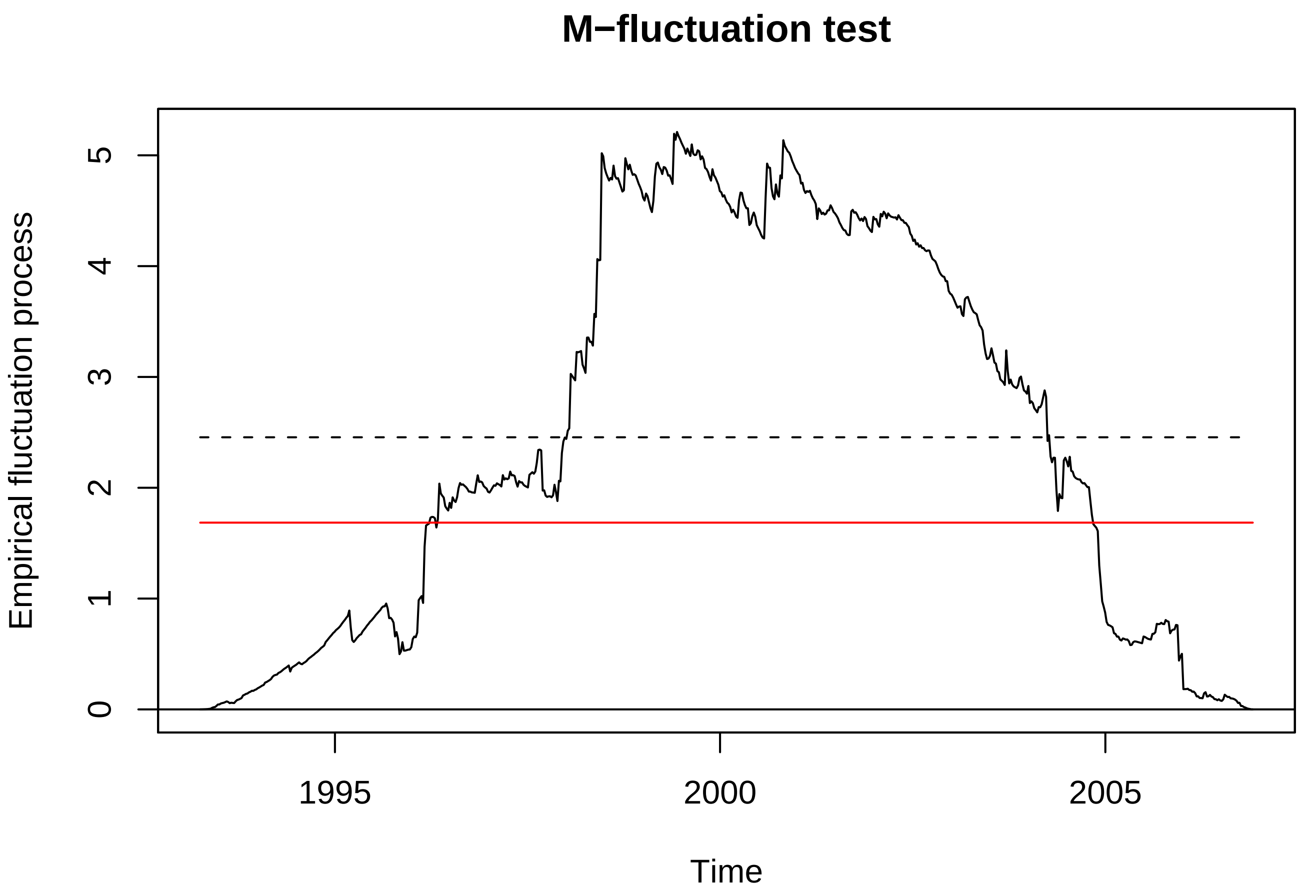
```
R> inr_lm <- fxlm(INR ~ USD + JPY + EUR + GBP,
+     data = inr)
```

which is subsequently assessed using the Nyblom-Hansen test

```
R> inr_efp <- gefp(inr_lm, fit = NULL)
R> plot(inr_efp, functional = meanL2BB)
```

leading to a test statistic of 2.456 ($p < 0.001$).

Indian FX regimes



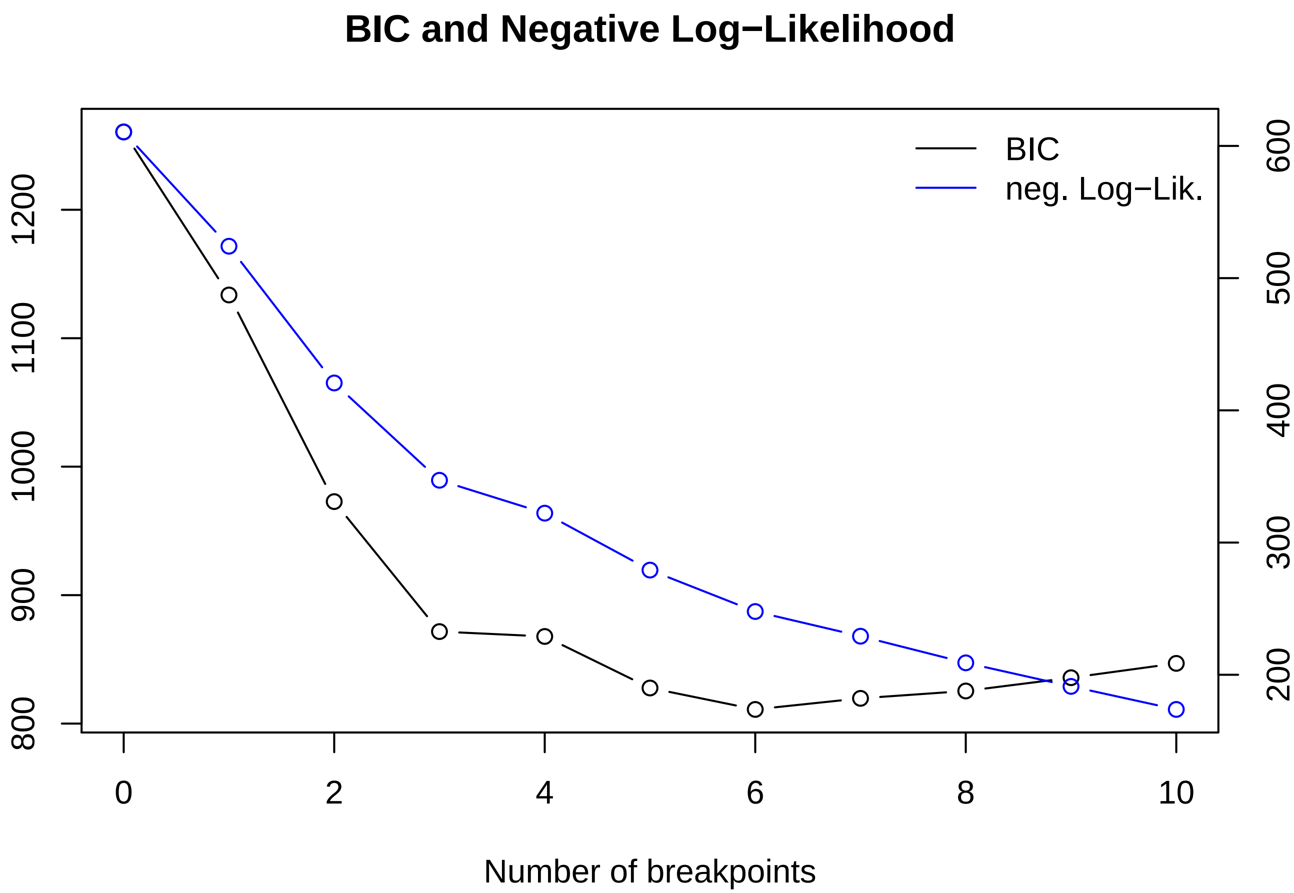
Indian FX regimes

Given the clear evidence of structural instability of the FX regime, it should be determined what reasonable breakpoints are:

```
R> inr_reg <- fxregimes(INR ~ USD + JPY + EUR +
+     GBP, data = inr, h = 20, breaks = 10)
R> plot(inr_reg)
```

The BIC would select $m = 6$ breakpoints. However, given the kink in the BIC curve, it seems to be reasonable to inspect the $m = 3$ breakpoints model as well.

Indian FX regimes



Indian FX regimes

	(Intercept)	USD	JPY	EUR	GBP	(Std. Error)
1993-04-09--1995-03-03	-0.006	0.972	0.023	0.011	0.020	0.157
1995-03-10--1998-08-21	0.161	0.943	0.067	-0.026	0.042	0.924
1998-08-28--2004-03-19	0.019	0.993	0.010	0.098	-0.003	0.275
2004-03-26--2006-12-01	-0.020	0.746	0.240	0.203	0.087	0.530

revealing the following FX regimes:

1. tight USD peg,
2. flexible USD peg,
3. tight USD peg,
4. flexible basket peg.

The solution with $m = 6$ breakpoints is, in fact, similar. Only the second regime is partitioned into further segments.

Indian FX regimes

	(Intercept)	USD	JPY	EUR	GBP	(Std. Error)
1993-04-09--1994-05-27	-0.014	0.981	0.020	0.004	0.044	0.098
1994-06-03--1995-08-25	0.017	0.885	0.000	0.196	0.078	0.286
1995-09-01--1996-08-09	0.174	1.167	0.353	-0.791	-0.036	1.224
1996-08-16--1997-08-15	0.011	1.010	-0.013	-0.102	0.035	0.197
1997-08-22--1998-08-21	0.365	0.704	-0.043	0.672	-0.043	0.967
1998-08-28--2004-03-19	0.019	0.993	0.010	0.098	-0.003	0.275
2004-03-26--2006-12-01	-0.020	0.746	0.240	0.203	0.087	0.530

Software

All methods are implemented in the R system for statistical computing and graphics

`http://www.R-project.org/`

in the contributed packages **strucchange** available from CRAN and **fxregime** which is under development at R-Forge.

`http://CRAN.R-project.org/`
`http://R-Forge.R-project.org/`

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Haldane AG, Hall SG (1991). “Sterling’s Relationship with the Dollar and the Deutschemark: 1976–89.” *The Economic Journal*, **101**, 436–443.

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