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Paper

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Exchange Rate Regime Analysis Using Structural Change Methods

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Abstract

Regression models for *de facto* currency regime classification are complemented by inferential techniques for tracking the stability of exchange rate regimes. Several structural change methods are adapted to these regressions: tools for assessing the stability of exchange rate regressions in historical data (*testing*), in incoming data (*monitoring*) and for determining the breakpoints of shifts in the exchange rate regime (*dating*). The tools are illustrated by investigating the Chinese exchange rate regime after China gave up on a fixed exchange rate to the US dollar in 2005 and to track the evolution of the Indian exchange rate regime since 1993.

Keywords: foreign exchange rates, CNY, INR, monitoring, dating.

1. Introduction

The exchange rate regime of a country determines how it manages its currency with respect to foreign currencies. Broadly speaking, exchange rate regimes range from *floating*, i.e., the currency is allowed to fluctuate based on market forces, *pegged*, i.e., the currency has limited flexibility when compared with a basket of currencies or a single currency, or *fixed*, i.e., the currency has a fixed parity to another currency.

In the last decade, the literature has revealed that the *de jure* exchange rate regime in operation in many countries that is announced by the central bank differs from the *de facto* regime in operation. This has motivated a small literature on data-driven methods for the classification of exchange rate regimes (see e.g., Reinhart and Rogoff 2004; Levy-Yeyati and Sturzenegger 2003; Calvo and Reinhart 2002). This literature has attempted to create datasets identifying the exchange rate regime in operation for all countries in recent decades, using a variety of alternative algorithms. While these classification schemes are widely used, the algorithms involve numerous ad-hoc constants, and are relatively weak on their statistical foundations.

A valuable tool for understanding the de facto exchange rate regime in operation is a linear regression model based on cross-currency exchange rates (with respect to a suitable numeraire). Used at least since Haldane and Hall (1991), this model was popularized by Frankel and Wei (1994) (and is hence also called Frankel-Wei model). Recent applications include Bénassy-Quéré, Coeuré, and Mignon (2006), Shah, Zeileis, and Patnaik (2005) and Frankel and Wei (2007).

To understand the de facto exchange rate regime in a given country in a given time period, researchers and practitioners can easily fit this regression model to a given data window, or use rolling data windows. However, such a strategy lacks a formal inferential framework for determining changes in the regimes. In this paper, we provide such a framework by adapting structural change tools from the statistics and econometrics literature to the specific challenges of exchange rate regressions. More precisely, we aim to answer the following questions:

1. Is a given exchange rate model stable within the time period in which it was established?

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2. If it is stable, does it remain stable for future incoming observations?
3. If it is not stable, when and how did the exchange rate regime change?

The first question amounts to *testing* for structural change (see e.g., Andrews 1993; Hansen 2001; Zeileis 2005), the second to *monitoring* structural change (see e.g., Chu, Stinchcombe, and White 1996; Zeileis, Leisch, Kleiber, and Hornik 2005), and the third to estimating breakpoints also known as *dating* structural changes (see e.g., Bai 1997; Bai and Perron 2003). These techniques are well-established for inference about the coefficients in least-squares regression. However, for the exchange rate regression, changes in the error variance are of prime interest. Therefore, we extend all techniques to incorporate the error variance as a full model parameter by adopting an (approximately) normal model.

Subsequently, the suggested techniques are applied to investigate the exchange rate regimes of two currencies: First, we assess the evolution of China's exchange rate regime after abandoning a fixed exchange rate between the Chinese yuan CNY and the US dollar USD (PBC 2005a). Second, the number and structure of exchange rate regimes for the Indian rupee INR since April 1993 is analyzed.

2. Methods

In this section, we briefly outline the standard model for exchange rate regression and subsequently present new procedures for assessing their stability. Methods for testing, monitoring and dating structural changes are derived by adapting existing methods for least-squares regression to regression for (approximately) normal data (including the error variance as a full model parameter).

2.1. Regression

To determine whether a certain currency is pegged to (a basket of) other currencies, the exchange rate regression (Frankel and Wei 1994) employs a standard linear regression model

$$y_i \quad = \quad x_i^\top \beta \; + \; u_i \qquad (i = 1, \dots, n), \tag{1}$$

in which the y_i are returns of the target currency and the x_i are vectors of returns for a basket of k currencies plus a constant.

When a country runs a fixed exchange rate, one element of β is 1 and the remaining elements are zero, and $\sigma^2 = 0$. When a country runs a pegged exchange rate against one currency, one element of β is near 1, the remaining elements are near zero, and σ^2 takes low values. With a basket peg, σ^2 takes low values, and the coefficients β correspond to weights of the basket. With a floating rate, σ^2 is high, and the β values reflect the natural current account and capital account linkages of the country.

For both y_i and x_i, we use log-difference returns (in percent) of different currencies as computed by $100 \cdot (\log p_i - \log p_{i-1})$, where p_i is the price of a currency at time i and given in some numeraire currency. For the numeraire, various choices are conceivable: e.g., a remote currency such as the Swiss franc CHF, a weighted index such as the special drawing rights SDR or some other standard such as gold. Typically, models with different numeraires will yield very similar results, especially if the underlying regime is a rigid basket peg (Frankel and Wei 1994, 2007). In our empirical applications, we use CHF as the numeraire and consistently use ISO 4217 abbreviations to denote currency returns computed from prices in CHF.

The exchange rate regression model from Equation 1 is typically estimated by ordinary least squares (OLS), often leading to unusually good model fits (even exceeding R^2 values of 99%) if a tight peg is recovered.

In the following, the econometrics of structural change is brought to bear in thinking about the stability of the full combined model parameter $\theta = (\beta^\top, \sigma^2)^\top$.

2.2. Testing

The classical question in structural change analysis is whether the true model parameter θ is really stable throughout the sample period $i = 1, \dots, n$. Thus, testing for structural change is concerned with testing the null hypothesis

$$H_0: \quad \theta_i = \theta_0 \quad (i = 1, \dots, n), \tag{2}$$

against the alternative that θ_i changes over time.

Various types of test statistics have been suggested for this hypothesis, e.g., based on residuals, parameter estimates, test statistics or estimating functions (see e.g., Hansen 2001; Zeileis 2005, and the references therein). Many of these are designed for testing the constancy of the regression coefficients β only, treating the error variance σ^2 as a nuisance parameter.

Here, we follow the approach of the Nyblom-Hansen test (Nyblom 1989; Hansen 1992) and use the estimating functions for deriving a test statistic. This allows conveniently for integrating the variance as a full model parameter. In addition to the estimating function (i.e., the gradient of the objective function, also known as model score) ψ_β for the regression coefficients in OLS regression, we simply employ another estimating function ψ_{σ^2} for the error variance:

$$\psi_\beta(y, x, \beta) \quad = \quad (y - x^\top \beta)\, x, \tag{3}$$

$$\psi_{\sigma^2}(y, x, \beta, \sigma^2) \quad = \quad (y - x^\top \beta)^2 - \sigma^2. \tag{4}$$

Note that these estimating functions are equivalent to employing maximum likelihood (ML) estimation in a normal regression, but can also be motivated by a quasi-ML approach for approximately normal data. Solving the corresponding estimation equations (by setting the sum of estimating functions to zero) yields the full sample estimates: $\hat\beta$ is the OLS or, equivalently, ML estimate; $\hat\sigma^2$ is the un-adjusted mean of the squared residuals or, equivalently, the ML estimate.

Deviations from parameter stability can be brought out by assessing deviations of the empirical estimating functions

$$\hat\psi_i \quad = \quad (\psi_\beta(y_i, x_i, \hat\beta)^\top, \psi_{\sigma^2}(y_i, x_i, \hat\beta, \hat\sigma^2))^\top$$

from their zero mean. Departures from zero are captured in a cumulative sum process

$$\mathit{efp}(t) \quad = \quad \hat V^{-1/2}\, n^{-1/2} \sum_{i=1}^{\lfloor nt \rfloor} \hat\psi_i \qquad (0 \le t \le 1), \tag{5}$$

scaled by a suitable estimate $\hat V$ of the covariance matrix of the estimating functions. Under the null hypothesis of parameter stability, this empirical fluctuation process is governed by a functional central limit theorem (FCLT): $\mathit{efp}(t)$ converges to a $(k+2)$-dimensional Brownian bridge $W^0(t)$ ($t \in [0,1]$) with a direct correspondence between the components of the process and the parameters (coefficients for the k currencies in the basket, intercept, and variance).

Various functionals are conceivable for aggregating this fluctuation process to a scalar test statistic. Below, we simply use a double maximum statistic (over parameters and time) because it can easily be visualized along with critical values from the distribution of the maximum of a Brownian bridge. However, other functionals can just as easily be applied, e.g., a Cramér-von Mises statistic as in the Nyblom-Hansen test (Nyblom 1989; Hansen 1992) or a sup LM statistic (Andrews 1993) or a MOSUM-type statistic:

$$\begin{aligned}
S_{dmax} &= \sup_{t \in [0,1]} ||\mathit{efp}(t)||_\infty, \\
S_{CvM} &= n^{-1} \sum_{i=1}^{n} ||\mathit{efp}(i/n)||_2^2, \\
S_{\sup LM} &= \sup_{t \in \Pi} \frac{||\mathit{efp}(t)||_2^2}{t(1-t)}, \\
S_{MOSUM} &= \sup_{t \in [0,1]} ||\mathit{efp}(t+h) - \mathit{efp}(t)||_\infty,
\end{aligned}$$

where h is the bandwidth of the MOSUM test and Π is a compact subset of $[0,1]$ derived by trimming a certain fraction of observations.

The $\sup LM$ test would be particularly well-suited for single break alternatives, MOSUM and Cramér-von Mises statistics are likely to perform better under multiple shifts. Below, the double maximum statistic is used due to its interpretability. Critical values can be obtained for each statistic from the corresponding limiting distributions, see Zeileis (2005) for a unified approach.

2.3. Monitoring

Given that a stable model could be established for observations $i = 1, \dots, n$, it is natural to ask whether this model remains stable for future incoming observations $i > n$. More formally, monitoring (Chu *et al.* 1996) tests the null hypothesis

$$H_0: \quad \theta_i = \theta_0 \quad (i > n), \tag{6}$$

sequentially against changes in the so-called monitoring period $i > n$ (or the scaled $t > 1$).

Given the tools from the previous section, an extension to the monitoring situation is fairly straightforward. The empirical fluctuation process $efp(t)$ is simply continued in the monitoring period by computing the empirical estimating functions for each new observation (using the parameter estimates from the stable history period) and updating the cumulative sum process. This is still governed by an FCLT (Zeileis 2005) from which suitable boundaries can be computed that are crossed with only a given probability under the null hypothesis. Below, we adopt a simple linear boundary function $b(t) = \pm c \cdot t$ as suggested in Zeileis *et al.* (2005). Thus, we detect a change if

$$\sup_{t \in [1,T]} \left|\left| \frac{efp(t)}{t} \right|\right|_\infty$$

exceeds some critical value c (which can be obained from Zeileis *et al.* 2005, Table III). Again, other boundaries could be chosen for directing power against other particular alternatives.

2.4. Dating

Given evidence for parameter instability in the exchange rate regression, a natural question is to ask when the regime changes, i.e., to estimate the breakpoints in the model. Breaks (rather than smooth transitions) are particularly likely to be a useful model here because changes in the exchange rate regime typically stem from policy interventions of the corresponding central banks.

A straightforward estimation algorithm for such a segmented exchange rate regime is to optimize a segmented objective function over all conceivable partitions. Bai and Perron (2003) describe a dynamic programming algorithm for optimizing the segmented residual sum of squares (RSS) in linear regression models. This approach treats the variance as a nuisance parameter and is thus not really sensitive to changes in the variance which would be a desirable property for segmenting exchange rate regressions. Therefore, we employ the same idea as before for deriving the estimating functions and adopt an (approximately) normal model. Instead of using the objective function Ψ_{RSS} like Bai and Perron (2003) which depends only on the regression coefficients, we use the corresponding negative log-likelihood Ψ_{NLL} which also incorporates the error variance σ^2:

$$\Psi_{\text{RSS}}(\beta) = \sum_i (y_i - x_i^\top \beta)^2, \tag{7}$$

$$\Psi_{\text{NLL}}(\beta, \sigma) = \sum_i -\log\left(\sigma^{-1}\phi\left(\frac{y_i - x_i^\top\beta}{\sigma}\right)\right), \tag{8}$$

where $\phi(\cdot)$ is the probability density function of the standard normal distribution. Note that both objective functions are suitable anti-derivatives (modulo scaling) of ψ_β and Ψ_{NLL} is additionally an anti-derivative for ψ_{σ^2}.

To optimize all model parameters—in a model with m breaks, there are $(m+1)(k+2)$ regression parameters plus m breakpoints—simultaneously, Bai and Perron (2003) discuss a dynamic programming algorithm. The same algorithm can applied here because Ψ_{NLL} is also an objective function that is additive in the observations (Hawkins 2001). More precisely, we denote the negative log-likelihood (NLL) associated with a set of m breakpoints as

$$NLL(i_1, \dots, i_m) \quad = \quad \sum_{j=1}^{m+1} nll(i_{j-1}+1, i_j), \tag{9}$$

where $nll(i_{j-1}+1, i_j) = \Psi_{\mathrm{NLL}}(\hat{\beta}^{(j)}, \hat{\sigma}^{(j)})$ is the evaluation of the optimal objective function on the j-th segment with observations $i_{j-1}+1, \dots, i_j$ ($i_0 = 0$ and $i_{m+1} = n$). and segment-specific parameter estimates. The optimal partition of m breakpoints from n observations (with respect to NLL) is then defined by minimizing

$$\mathcal{I}_{m,n} \quad = \quad \operatorname*{argmin}_{(i_1,\dots,i_m)} NLL(i_1, \dots, i_m). \tag{10}$$

subject to a minimal segment size condition $i_j - i_{j-1} + 1 \ge n_h \ge k+2$. To avoid solving the problem above by a full grid search of order $O(n^m)$, a more efficient dynamic programming algorithm of order $O(n^2)$ can be utilized that exploits Bellman's principle: the optimal segmentation satisfies the recursion

$$NLL(\mathcal{I}_{m,n}) \quad = \quad \min_{mn_h < i \le n - n_h} [NLL(\mathcal{I}_{m-1,i}) + nll(i+1, n)]. \tag{11}$$

This can be solved based on a triangular matrix of $nll(i,j)$ with $j - i \ge n_h$ which can be set up even more cheaply if recursive residuals are employed in the computation of the NLL.

Using this algorithm, the ML segmentation can be computed if the number of breakpoints m is known. In practice, however, m typically needs to be chosen based on the observed data as well. One solution to this problem is to compute the optimal segmentations for a sequence of breakpoints $m = 0, 1, \dots$ (which can all be computed from the same triangular matrix mentioned above) and to choose m by optimizing some information criterion $IC(m)$. As the segmentations are likelihood-based, such information criteria are easily available as

$$IC(m) \quad = \quad 2 \cdot NLL(\mathcal{I}_{m,n}) \; + \; \text{penalty} \cdot ((m+1)(k+2) + m)\,,$$

with different penalties leading to different information criteria. Bai and Perron (2003) consider two different criteria, the BIC and a modified BIC as suggested by Liu, Wu, and Zidek (1997):

$$\begin{aligned} \text{penalty}_{\text{BIC}} \quad &= \quad \log(n), \\ \text{penalty}_{\text{LWZ}} \quad &= \quad \alpha \cdot \log(n)^{2+\delta}. \end{aligned}$$

We follow the recommendations of Bai and Perron (2003) and Liu *et al.* (1997) and use the LWZ criterion in our empirical studies, setting the parameters $\alpha = 0.299$ and $\delta = 0.1$ so that the LWZ penalty is higher than in the BIC for $n > 20$.

3. Applications

In this section, the methods presented above are applied to investigate the exchange rate regimes of China and India. The cross-currency returns are derived from exchange rates available online from the US Federal Reserve at `http://www.federalreserve.gov/releases/h10/Hist/`. All computations are carried out in the R system for statistical computing (R Development Core Team 2007, version 2.5.1) with packages **fxregime** 0.1-0 (Zeileis, Shah, and Patnaik 2007) and **strucchange** 1.3-2 (Zeileis, Leisch, Hornik, and Kleiber 2002). Both, R itself and the packages, are freely available at no cost under the terms of the GNU General Public Licence (GPL) from the Comprehensive R Archive Network at `http://CRAN.R-project.org/`. Vignettes reproducing the analysis from this paper are available via `vignette("CNY", package = "fxregime")` and `vignette("INR", package = "fxregime")` after installing the packages.

3.1. China

In recent years, there has been enormous global interest in the CNY exchange rate which was fixed to the USD in the years leading up to mid-2005. In July 2005, China announced a small appreciation of CNY, and, in addition, a reform of the exchange rate regime. The People's Bank of China (PBC) announced this reform to involve a shift away from the fixed exchange rate to a basket of currencies with greater flexibility (PBC 2005a). In August 2005, PBC (2005b) also announced that USD, JPY (Japanese yen), EUR (euro) and KRW (Korean won) would be the currencies in this basket. Further currencies announced to be of interest are GBP (British pound), MYR (Malaysian ringgit), Singapore dollar (SGD), RUB (Russian ruble), AUD (Austrialian dollar), THB (Thailand baht) and CAD (Canadian dollar).

Despite the announcements of the PBC, little evidence could be found for China moving away from a USD peg in the months after July 2005 (Shah *et al.* 2005). To begin our investigation here, we follow up on our own analysis from autumn 2005: Using daily returns from 2005-07-26 up to 2005-10-31 (corresponding to $n = 68$), we established a stable exchange regression in Shah *et al.* (2005) that we monitored in the subsequent months, publishing the monitoring progress weekly online at http://www.mayin.org/ajayshah/papers/CNY_regime/. Here, we report on the findings of this project using the same settings with only slightly modified currency basket. The currencies considered are the four first-tier currencies announced (USD, JPY, EUR, KRW) as well two further currencies (GBP, MYR) considered potentially interesting previously (Shah *et al.* 2005; Frankel and Wei 2007). We do not use all eleven currencies because including irrelevant currencies decreases power and precision of the procedures and the most important conclusions can already be drawn with a much smaller basket, as we will see below.

In a first step, we fit the exchange regression to the 68 observations in the first three months after the announcements of the PBC. The estimated exchange rate regime is

$$\begin{aligned} \mathrm{CNY}_i \;&=\; -0.005 \,+\, 0.968\,\mathrm{USD}_i \,+\, 0.002\,\mathrm{JPY}_i \,-\, 0.019\,\mathrm{EUR}_i \\ &\quad -\, 0.008\,\mathrm{GBP}_i \,+\, 0.009\,\mathrm{KRW}_i \,+\, 0.027\,\mathrm{MYR}_i \,+\, \hat{u}_i. \end{aligned}$$

with only the USD coefficient differing significantly from 0 (but not significantly from 1), thus signalling a very clear USD peg. The R^2 of the regression is 99.8% due to the extremely low standard deviation of $\sigma = 0.028$.

The fluctuation in the parameters during this history period is very small, see the corresponding $\mathit{efp}(t)$ for $0 \le t \le 1$ in Figure 1 on the left of the vertical dashed line (marking the end of the history period). Also none of the parameter instability tests from Section 2.2 would reject the null hypothesis of stability, e.g., the double maximum statistic is $S_{dmax} = 1.086$ with a p value of $p = 0.813$.

The same fluctuation process $\mathit{efp}(t)$ is continued subsequently as described in Section 2.3 in the monitoring period starting from 2005-11-01 as shown in Figure 1 on the right of the vertical dashed line. The boundary shown is $b(t) = \pm 2.55 \cdot t$, derived at 5% significance level (for monitoring up to $T = 4$). In the first months, up to spring 2006, there is still moderate fluctuation in all processes signalling no departure from the previously established USD peg. In fact, the only larger deviation during that time period is surprisingly a *decrease* in the variance—corresponding to a somewhat tighter USD peg—which almost leads to a boundary crossing in January 2006. However, the situation relaxes a bit before in March 2006 several components of the fluctuation process start to deviate clearly from their mean: The largest deviation is in the variance, slightly smaller deviations can be seen for the USD and MYR coefficients. Note that the USD coefficient, corresponding to its weight in the currency basket, decreases while the MYR coefficient increases. The earliest crossing is for the MYR coefficient (that starts to deviate a bit earlier than the other two parameters) in 2006-03-15. All other coefficients stay away rather clearly from their boundaries. Some slight (and still non-significant) movement can only be seen in KRW.

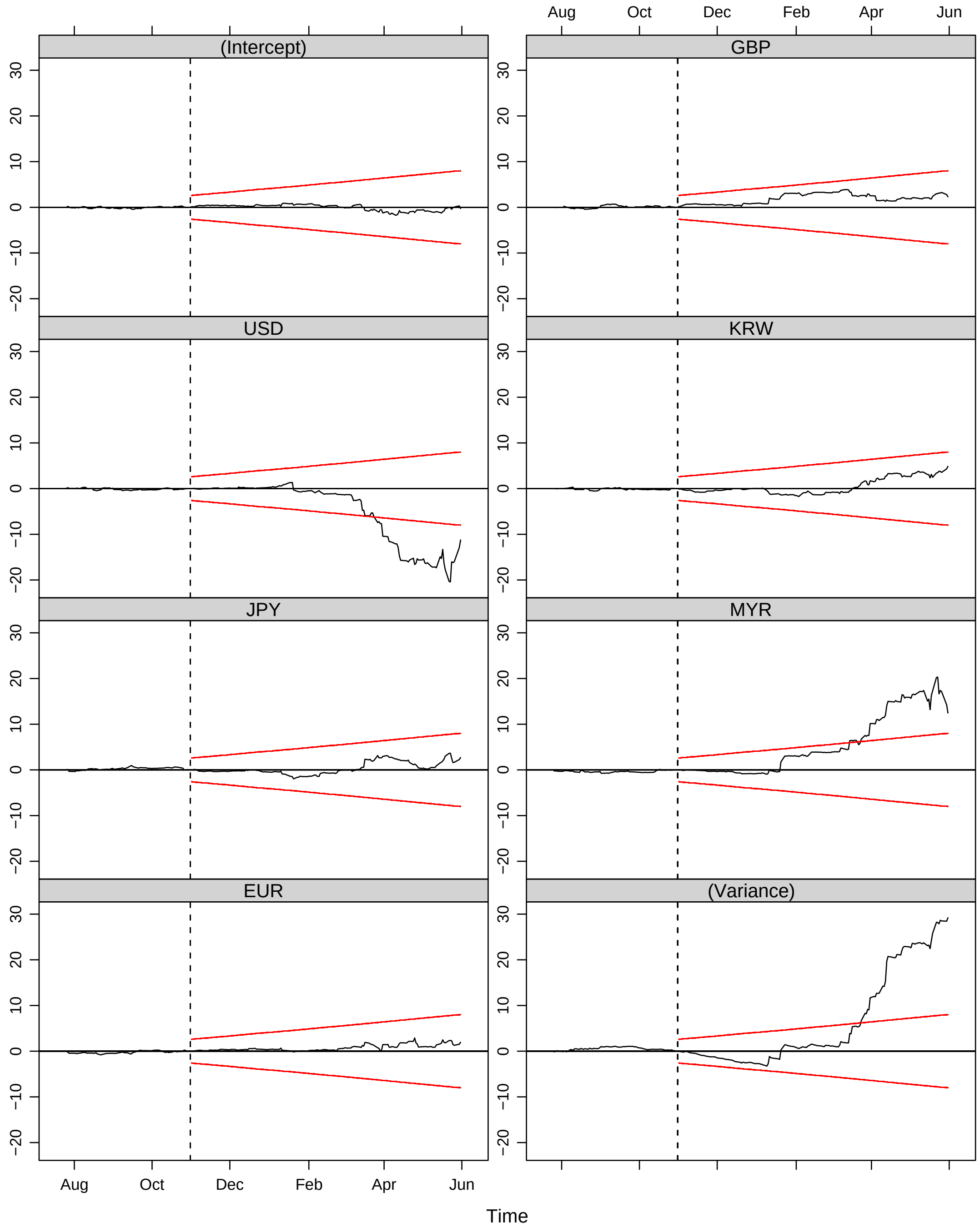

Figure 1: Monitoring fluctuation process for CNY exchange rate regime.

To capture the changes in China's exchange rate regime more formally, we fit a segmented exchange rate regression by dating regime changes as described in Section 2.4. Using daily returns from 2005-07-26 through to 2007-06-07, we determine the optimal breakpoints for $m = 1, \dots, 10$ breaks with a minimal segment size of $n_h = 20$ observations and compute the associated segmented NLL and LWZ criterion. Of course, NLL decreases with every additional break but with a marked

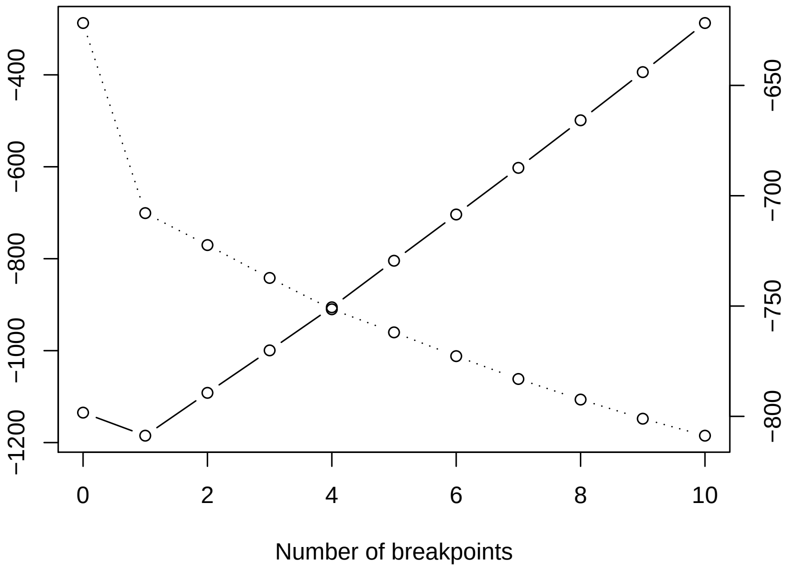

Figure 2: Negative log-likelihood (dotted, left axis) and LWZ information criterion (solid, right axis) for CNY exchange rate regimes.

decrease only for going from $m = 0$ to 1 break. This is also reflected in the LWZ criterion that assumes its minimum for $m = 1$ so that we choose a 1-break (or 2-segment) model. The estimated breakpoint is 2006-03-14, i.e., just one day before the boundary crossing in the monitoring procedure, confirming the findings above. The associated parameter estimates are provided in Table 1 along with standard errors (in parantheses). Coefficients significant at 5% level are printed in bold face. These results allow for several conclusions about the Chinese exchange rate regime after spring 2006: CNY is still closely linked to USD. The exchange rate regime got much more flexible increasing from $\sigma = 0.027$ to 0.076 which is still very low, even compared with other pegged exchange rate regimes (see results below for India). The intercept is significantly smaller than 0, reflecting a slow appreciation of the CNY. There is some small but significant weight on KRW and MYR, however no weight at all in the other currencies JPY, EUR and GBP. Unfortunately, there is a small deviation from a plain USD peg also in the first period before spring 2006. The reason is that the change in the MYR coefficient occurs slightly earlier than for the USD coefficient and the variance σ^2. Nevertheless, the change is captured well enough for practical purposes (albeit not completely perfect) in a 2-segment model signalling a modest liberation of the rigid USD peg in spring 2006. To assess whether the CNY regime makes further steps away from tight pegging to USD, a new monitoring process could be set up using the data after 2006-03-14 as the history

period	β_0	β_{USD}	β_{JPY}	β_{EUR}	β_{GBP}	β_{KRW}	β_{MYR}	σ
2005-07-26 – 2006-03-14	-0.004	**0.923**	0.003	-0.012	0.005	0.006	**0.072**	0.027
	(0.002)	(0.025)	(0.005)	(0.016)	(0.008)	(0.006)	(0.024)	
2006-03-15 – 2007-06-07	**-0.015**	**0.921**	-0.004	-0.023	-0.020	**0.042**	**0.042**	0.076
	(0.004)	(0.020)	(0.012)	(0.030)	(0.017)	(0.015)	(0.021)	

Table 1: Segmented CNY exchange rate regimes.

period (or potentially bounding the start a bit away from the break).

3.2. India

Another expanding economy with a currency that has been receiving increased interest over the last years is India. As with China, India is in the process of evolving away from a closed economy towards a greater integration with the world on both the current account and the capital account. This has brought considerable stress upon the pegged exchange rate regime.

Therefore, we try to track the evolution of the INR exchange rate regime since trading in the INR began. Using weekly returns from 1993-04-09 through to 2007-06-08 (yielding $n = 740$ observations), we first fit a single exchange regime that is subsequently segmented. Weekly rather than daily returns are employed to reduce the noise in the data and alleviate the computational burden of the dating algorithm of order $O(n^2)$. The currency basket employed is essentially the same as above, using the most important floating currencies as well as two further important Asian currencies. The only difference to the previous section is that EUR can only be used for the time after its introduction as official euro-zone currency in 1999. For the time before, exchange rates of the German mark (DEM, the most important currency in the EUR zone) adjusted to EUR rates, are employed. The combined returns are denoted DUR below.

Using the full sample, we establish a single exchange rate regression only to show that there is not a single stable regime and to gain some exploratory insights from the associated fluctuation process. As we do not expect to be able to draw valid conclusions from the coefficients of a single regression, we do not report the coefficients here and rather move on to a visualization of $efp(t)$ and the associated double maximum test in Figure 3. Because two processes (intercept and variance) exceed their 5% level boundaries, there is evidence for at least one structural change. More formally, the test statistic is $S_{dmax} = 1.764$ with a p value of $p = 0.031$. This p value is not very small because there seem to be several changes in various parameters. A more suitable test in such a situation would be the Nyblom-Hansen test with $S_{CvM} = 2.805$ and $p < 0.005$. However, the multivariate fluctuation process is interesting as a visualization of the changes in the different parameters. The process for the variance σ^2 has the most distinctive shape revealing at least four different regimes: at first, a variance that is lower than the overall average (and hence a decreasing process), then a much larger variance (up to the boundary crossing), a much smaller variance again and finally a period where the variance is roughly the full-sample average. Other interesting processes are the intercept and maybe the USD and DUR. The latter two are not significant but have some peaks revealing a decrease and increase, respectively, in the corresponding coefficients.

To capture this exploratory assessment in a formal way, a dating procedure is conducted for $m = 1, \dots, 10$ breaks and a minimal segment size of $n_h = 20$ observations. The resulting values for the NLL and associated LWZ information criterion are depicted in Figure 4. NLL is decreasing quickly up to $m = 3$ breaks with a kink in the slope afterwards. Similarly, LWZ takes its minimum for $m = 3$ breaks, choosing a 4-segment model. The corresponding parameter estimates are reported (along with estimated standard errors for the coefficients) in Table 2.

The most striking observation from the segmented coefficients is that INR was closely pegged to USD up to March 2004 when it shifted to a basket peg in which USD has still the highest weight but considerably less than before. Furthermore, the changes in σ are remarkable, roughly matching the exploratory observations from the empirical fluctuation process. A more detailed look at the results in Table 2 shows that the first period is a clear and tight USD peg. During that time, pressure to appreciate was blocked by purchases of USD by the central bank. The second period, including the time of the East Asian crisis, saw a highly increased flexibility in the exchange rates. Although the Reserve Bank of India (RBI) made public statements about managing volatility on the currency market, the credibility of these statements were low in the eyes of the market. The third period exposes much tighter pegging again with low volatility, some appreciation and some small (but significant) weight on DUR. In the fourth period after March 2004, India moved away from the tight USD peg to a basket peg involving several currencies with greater flexibility (but smaller than in the second period). In this period, reserves in excess of 20% of GDP were held by

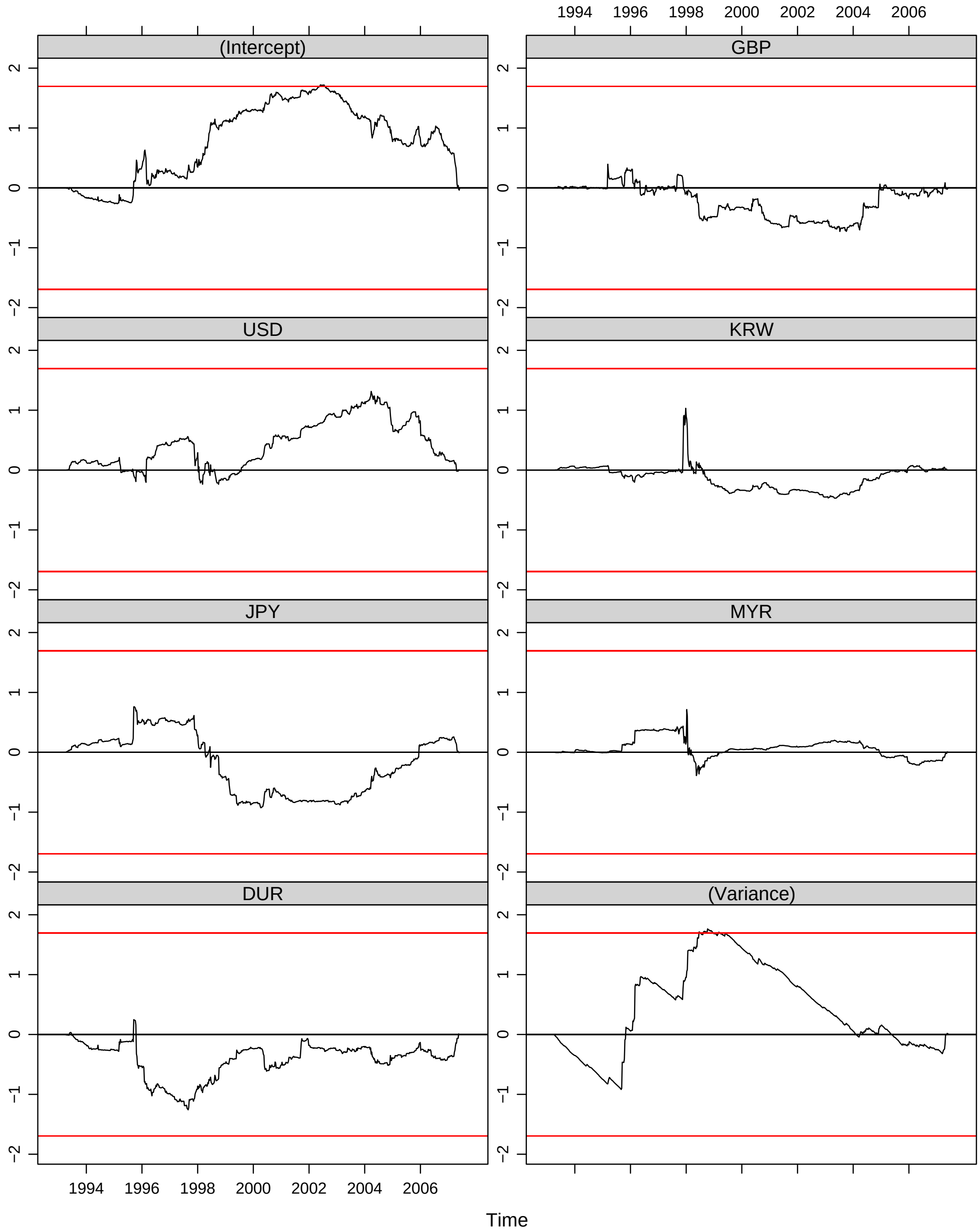

Figure 3: Historical fluctuation process for INR exchange rate regime.

the RBI, and a modest pace of reserves accumulation has continued.

In addition to revealing the evolution of the Indian exchange rate regime, the results are also interesting in comparison to the results for CNY. The tight USD peg in the first and the flexible basket peg in the last period for INR help to put the CNY results into persepctive, both in terms

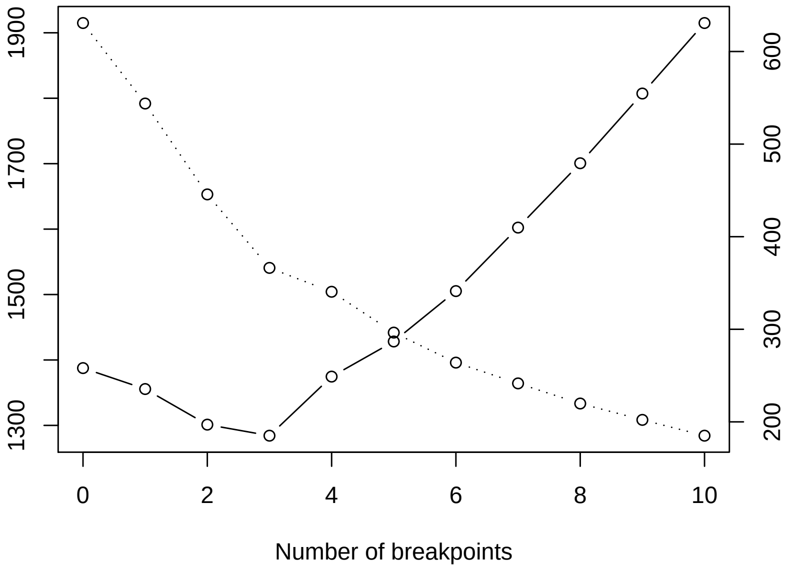

Figure 4: Negative log-likelihood (dotted, left axis) and LWZ information criterion (solid, right axis) for INR exchange rate regimes.

of the coefficients β and the standard deviation σ: The changes in the CNY regime are much more modest than for other pegged currencies such as the INR.

period	β_0	β_{USD}	β_{JPY}	β_{DUR}	β_{GBP}	β_{KRW}	β_{MYR}	σ
1993-04-09 – 1995-03-03	-0.006	**1.076**	0.020	0.010	0.017	-0.082	-0.022	0.156
	(0.017)	(0.081)	(0.014)	(0.032)	(0.025)	(0.073)	(0.021)	
1995-03-10 – 1998-08-21	**0.154**	**0.910**	0.075	-0.019	0.043	**0.070**	-0.052	0.901
	(0.069)	(0.074)	(0.049)	(0.152)	(0.080)	(0.024)	(0.029)	
1998-08-28 – 2004-03-19	0.019	**0.966**	0.003	**0.093**	-0.004	0.022	0.012	0.274
	(0.016)	(0.035)	(0.011)	(0.034)	(0.021)	(0.017)	(0.029)	
2004-03-26 – 2007-06-08	-0.029	**0.412**	**0.160**	**0.304**	0.082	**0.150**	**0.268**	0.544
	(0.045)	(0.131)	(0.049)	(0.126)	(0.062)	(0.062)	(0.135)	

Table 2: Segmented INR exchange rate regimes.

The existing literature classifies the INR is a *de facto* pegged exchange rate to the USD in the period after April 1993 (Reinhart and Rogoff 2004). Table 2 shows the fine structure of this pegged exchange rate; it supplies dates demarcating the four phases of the exchange rate regime; and it finds that by the fourth period, there was a basket peg in operation. This constitutes a statistically well-founded alternative to the existing classification schemes of the Indian exchange rate regime.

4. Summary

A formal inferential framework for data-driven assessment of the evolution of exchange rate regimes is presented. Based on a standard exchange rate regression model, new statistical procedures for testing the stability of exchange rate regimes in historical data, monitoring exchange rate regimes in incoming data and dating breaks between exchange rate regimes are suggested. Drawing on well-established structural change procedures for OLS regression, the techniques presented incorporate the error variance as a full model parameter of prime interest in exchange rate regimes by adopting a (quasi-)ML approach for (approximately) normal data. The techniques are applied to investigate the changes in the regimes of two currencies: CNY and INR. For the former, a 2-segment model is found for the time after July 2005 when China gave up on a fixed exchange rate to the USD. While being still closely linked to USD in both periods, there has been a small step in the direction of the claims of the Chinese central bank: flexibility slightly increased while the weight of the USD in the currency basket slightly decreased. For INR, a 4-segment model is found with a close linkage of INR to USD in the first three periods (with tight/flexible/tight pegging, respectively) before moving to a more flexible basket peg in spring 2004.

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References

Andrews DWK (1993). "Tests for Parameter Instability and Structural Change with Unknown Change Point." *Econometrica*, **61**, 821–856.

Bai J (1997). "Estimation of a Change Point in Multiple Regression Models." *Review of Economics and Statistics*, **79**, 551–563.

Bai J, Perron P (2003). "Computation and Analysis of Multiple Structural Change Models." *Journal of Applied Econometrics*, **18**, 1–22.

Bénassy-Quéré A, Coeuré B, Mignon V (2006). "On the Identification of *De Facto* Currency Pegs." *Journal of the Japanese and International Economies*, **20**(1), 112–127.

Calvo GA, Reinhart CM (2002). "Fear of Floating." *Quarterly Journal of Economics*, **117**(2), 379–408.

Chu CSJ, Stinchcombe M, White H (1996). "Monitoring Structural Change." *Econometrica*, **64**(5).

Frankel J, Wei SJ (1994). "Yen Bloc or Dollar Bloc? Exchange Rate Policies of the East Asian Countries." In T Ito, A Krueger (eds.), "Macroeconomic Linkage: Savings, Exchange Rates and Capital Flows," University of Chicago Press.

Frankel JA, Wei SJ (2007). "Assessing China's Exchange Rate Regime." *Technical report*, NBER Working Paper 13100. URL http://www.nber.org/papers/w13100.pdf.

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

Hansen BE (1992). "Testing for Parameter Instability in Linear Models." *Journal of Policy Modeling*, **14**, 517–533.

Hansen BE (2001). "The New Econometrics of Structural Change: Dating Breaks in U.S. Labor Productivity." *Journal of Economic Perspectives*, **15**, 117–128.

Hawkins DM (2001). "Fitting Multiple Change-Point Models to Data." *Computational Statistics & Data Analysis*, **37**, 323–341.

Levy-Yeyati E, Sturzenegger F (2003). "To Float or to Fix: Evidence on the Impact of Exchange Rate Regimes on Growth." *American Economic Review*, **93**(4), 1173–1193.

Liu J, Wu S, Zidek JV (1997). "On Segmented Multivariate Regression." *Statistica Sinica*, **7**, 497–525.

Nyblom J (1989). "Testing for the Constancy of Parameters Over Time." *Journal of the American Statistical Association*, **84**, 223–230.

PBC (2005a). "Public Announcement of the People's Bank of China on Reforming the RMB Exchange Rate Regime." URL http://www.pbc.gov.cn/english/detail.asp?col=6400&ID=542.

PBC (2005b). "Speech of Governor Zhou Xiaochuan at the Inauguration Ceremony of the People's Bank of China Shanghai Head Office." URL http://www.pbc.gov.cn/english/detail.asp?col=6500&ID=82.

R Development Core Team (2007). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Reinhart CM, Rogoff KS (2004). "The Modern History of Exchange Rate Arrangements: A Reinterpretation." *The Quarterly Journal of Economics*, **117**, 1–48.

Shah A, Zeileis A, Patnaik I (2005). "What is the New Chinese Currency Regime?" *Report 23*, Department of Statistics and Mathematics, Wirtschaftsuniversität Wien, Research Report Series. URL http://epub.wu-wien.ac.at/dyn/openURL?id=oai:epub.wu-wien.ac.at:epub-wu-01_8b0.

Zeileis A (2005). "A Unified Approach to Structural Change Tests Based on ML Scores, F Statistics, and OLS Residuals." *Econometric Reviews*, **24**(4), 445–466.

Zeileis A, Leisch F, Hornik K, Kleiber C (2002). "**strucchange**: An R Package for Testing for Structural Change in Linear Regression Models." *Journal of Statistical Software*, **7**(2), 1–38. URL http://www.jstatsoft.org/v07/i02/.

Zeileis A, Leisch F, Kleiber C, Hornik K (2005). "Monitoring Structural Change in Dynamic Econometric Models." *Journal of Applied Econometrics*, **20**, 99–121.

Zeileis A, Shah A, Patnaik I (2007). **fxregime**: *Exchange Rate Regime Analysis*. R package version 0.1-0, URL http://CRAN.R-project.org/.