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Comment

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I. Introduction

The paper "Can Parameter Instability Explain the Meese-Rogoff Puzzle?" by Philippe Bacchetta, Eric van Wincoop, and Toni Beutler brings fresh air to a long-debated issue in international macroeconomics. The authors investigate whether exchange rate unpredictability is caused by instabilities of the relationship between exchange rates and its fundamentals. In their exercise, Bacchetta et al. calibrate on actual data a model in which the parameters linking exchange rates and fundamentals are allowed to change over time. They find that the pattern of out-of-sample (un)predictability assessed on data generated from a fixed coefficient model can roughly reproduce the features observed in the data. In addition, they find no significant differences in out-of-sample accuracy when data are generated by time-varying rather than fixed coefficients. A significant impact of parameter instability is found only when shifts in parameters are persistent, but in this case parameter instability increases rather than reduces predictability. On the basis of these findings, the authors conclude that exchange rate unpredictability is due to the weakness rather than to the instability of the relationship between exchange rates and fundamentals.

I like the general idea of the paper, but I am not quite convinced about the authors' conclusions. My main point is that Bacchetta et al. do not properly account for parameter instability.

Bacchetta et al. calibrate the model used for simulations in a way that does not allow for permanent shifts in the parameters. In their setup, the variance of parameters' innovations (σ_β^2) tends to become smaller when the parameters' autocorrelation (ρ_β^2) increases. Permanent shifts in the parameters are ruled out by construction because the unconditional variance of the parameters, $\sigma_\beta^2/(1-\rho_\beta^2)$, is kept fixed, and hence

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the model collapses to fix coefficients when structural changes tend to have permanent effects (i.e., $\sigma_\beta \rightarrow 0$ when $\rho_\beta \rightarrow 1$). In this setup the authors show that persistent parameter instability does not worsen forecasting accuracy; on the contrary, it induces substantial improvements.

However, there is no reason to think that structural changes are temporary. On the contrary, significant changes in the macroeconomic environment are very likely to last. In fact, in empirical works time-varying parameters are usually modeled as random walks (see Cogley and Sargent 2002, 2005; Primiceri 2005). It would be a mistake to immediately conclude from the results of Bacchetta et al. that the Meese-Rogoff puzzle is explained exclusively by the small-sample estimation bias. Before drawing this conclusion, one must appropriately study the case in which parameters shift permanently. This is the task I will undertake in this discussion.

I will consider a model in which structural changes are permanent by assuming that the parameters linking exchange rates and fundamentals evolve as random walks. Instead of resorting to calibration, which relies on ad hoc assumptions, the time-varying model used for simulation will be fully estimated. The design of any model with time-varying coefficients is rather problematic since it is hard to distinguish between strength and instabilities of the relationship between exchange rates. To overcome this problem, the estimation is performed using Bayesian techniques, and the allowed amount of time variation will be controlled for by setting the prior variance on the coefficient's innovations.

I will focus on forecasting the euro/U.S. dollar exchange rate using relative prices as fundamentals. Since fundamentals are likely to play an important role in explaining medium- to long-term fluctuations, the analysis will be performed by using annual data and taking into account the eventual dynamic adjustment to purchasing power parity equilibrium. Bacchetta et al. instead focus on short-horizon forecasts (1 month ahead) that are produced by exploiting only contemporaneous (within the month) correlations and neglecting the dynamic adjustment to long-run equilibria. As a consequence, the authors are likely to overemphasize the weakness of the relationship between the exchange rates and fundamentals.

II. Forecasting the Euro

Let s_t be the (log) exchange rate between the euro and the U.S. dollar (the source is OECD, National Accounts) and $\tilde{p}_t = p_t^{\mathrm{ea}} - p_t^{\mathrm{us}}$ be the (log) relative consumer prices between the Euro Area (ea) and the United States (us) (the source is OECD, Main Economic Indicators). In order to take into account the common trend between relative prices and the nominal exchange rate, I will consider a bivariate vector autoregressive (VAR) model for the real exchange rate $q_t = s_t - \tilde{p}_t$ and the inflation differential $\tilde{\pi}_t = \tilde{p}_t - \tilde{p}_{t-1}$. The sample ranges from 1975 to 2007. Prior to 1999, I will consider Germany and the deutsche mark instead of the Euro Area and the euro. Data are plotted in figure 1.

Denoting $y_t = [q_t, \tilde{\pi}_t]'$, we have

$$y_t = A_0 + A_1 y_{t-1} + e_t, \quad \varepsilon_t \sim N(0, \Sigma).$$

For simplicity, I will focus on the forecast of the real exchange rate q_t. Qualitative results are confirmed when forecasting the exchange rate itself. The exercise goes as follows. Let us forecast first the euro/dollar exchange rate in 1999, the year of the introduction of the euro. Parameters are estimated using data up to 1998 and samples of different length L. The shorter sample includes $L = 10$ years of data, from 1989 until 1998. The longest estimation sample starts in 1975 and includes $L = 24$ years of data. The estimated parameters are used to compute exchange rate forecasts. As in Bacchetta et al.'s paper, we focus on predictions that are conditional on actual future fundamentals, that is, assuming that relative prices, $\tilde{p}_t$, from 1999 onward were perfectly foreseen.[1] The forecasts are compared with the actual value of the real exchange rate in 1999. The same exercise is repeated every year to produce 1-year-ahead forecasts. Accuracy is measured by averaging the square forecast errors over the evaluation sample 1999–2007.

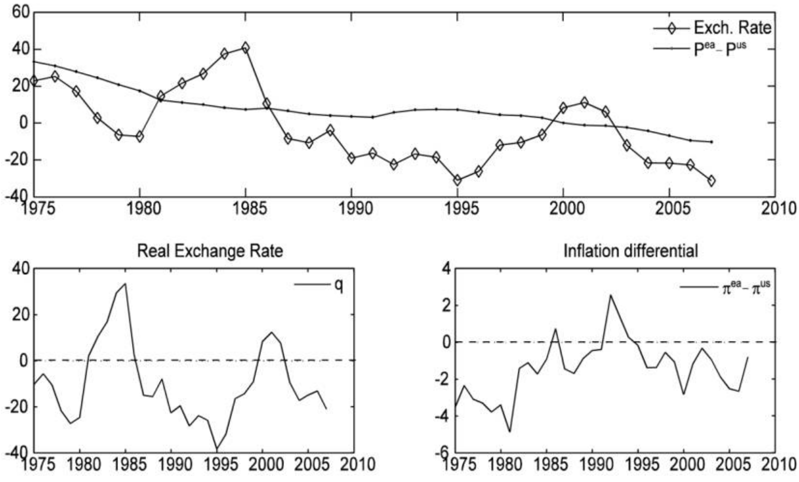

Fig. 1. The data

Figure 2 reports the mean square forecast error produced by the model relative to the random walk forecast. Results are plotted against the length L of the estimation sample. Numbers smaller than one indicate that model forecasts are more accurate than the random walk forecasts. Numbers larger than one indicate that forecast accuracy cannot be improved relative to the naive benchmark by exploiting information contained in the fundamentals. Looking at the performances across estimation samples of different length provides interesting insights into the trade-off between estimation error and structural instability since estimating the model using a few (many) years of data provides insurance against model instability, but at the same time it implies larger (smaller) parameter uncertainty.

With the shortest sample length the mean squared error of the model-based forecasts is twice the mean squared error of the random walk. Expanding the estimation sample first improves forecasting accuracy indicating a reduction of a parameter's estimation error. With a sample between 16 and 22 years around years, model-based forecasts outperform the random walk with maximum improvements of 40% when including 20 years of data for the estimation. When the sample is further increased, forecast accuracy deteriorates and the advantages of model-based forecasts relative to the random walk are lost, suggesting that the gains from reduced estimation error are counterbalanced by losses due to the presence of structural instabilities.

In summary, results indicate that out-of-sample accuracy does not improve monotonically when increasing the estimation sample but

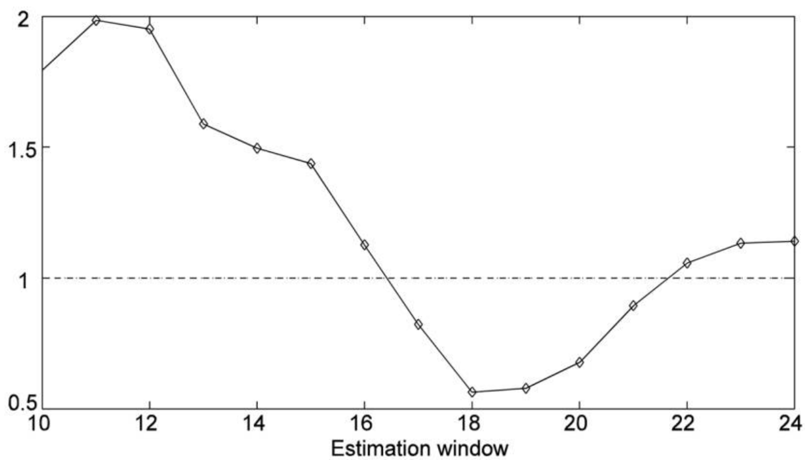

Fig. 2. The relative mean square forecast error

has a U shape signaling the presence of a trade-off between parameter instability and parameter uncertainty. In addition, for some estimation window the model-based forecasts are more accurate than the random walk forecasts.[2]

III. Inspecting the Role of Structural Instabilities

In order to assess the role played by structural instabilities in accounting for exchange rate unpredictability, I will estimate a VAR model with time-varying coefficients developed by Primiceri (2005). The model offers a parsimonious representation of prominent features of structural changes since it provides reliable descriptions of key macroeconomic aggregates (see Cogley, Primiceri, and Sargent 2008) and accurate out-of-sample predictions (see D'Agostino, Gambetti, and Giannone 2008).

I assume that y_t admits the following time-varying coefficients VAR(1) representation:

$$y_t = A_{0,t} + A_{1,t} y_{t-1} + \varepsilon_t, \tag{1}$$

where $A_{0,t}$ contains time-varying intercepts, $A_{1,t}$ are matrices of time-varying coefficients, and ε_t is a Gaussian white noise with zero mean and time-varying covariance matrix Σ_t. Let $A_t = [A_{0,t}, A_{1,t}]$ and $\theta_t = \text{vec}(A_t')$, where $\text{vec}(\cdot)$ is the column stacking operator. Conditional on such an assumption, θ_t is assumed to follow a random walk:

$$\theta_t = \theta_{t-1} + \omega_t, \tag{2}$$

where ω_t is a Gaussian white noise with zero mean and covariance Ω. Let $\Sigma_t = F_t D_t F_t'$, where F_t is lower triangular, with ones on the main diagonal, and D_t is a diagonal matrix. Denote by σ_t the vector of the diagonal elements of $D_t^{1/2}$ and $\phi_{i,t}$, $i = 1, \ldots, n-1$, the column vector formed by the nonzero and non-one elements of the $(i+1)$th row of F_t^{-1}. The standard deviations, σ_t, are assumed to evolve as geometric random walks, belonging to the class of models known as stochastic volatility. The simultaneous relations ϕ_{it} in each equation of the VAR are assumed to evolve as independent random walks:

$$\log \sigma_t = \log \sigma_{t-1} + \xi_t, \tag{3}$$

$$\phi_{i,t} = \phi_{i,t-1} + \psi_{i,t}, \tag{4}$$

where ξ_t and $\psi_{i,t}$ are Gaussian white noises with zero mean and covariance matrix Ξ and Ψ_i, respectively. Let $\phi_t = [\phi_{1,t}', \ldots, \phi_{n-1,t}']$,

$\psi_t = [\psi'_{1,t}, \ldots, \psi'_{n-1,t}]$, and Ψ be the covariance matrix of ψ_t; $\psi_{i,t}$ is assumed to be independent of $\psi_{j,t}$, for $j \neq i$. In addition, ξ_t, ψ_t, ω_t, and ε_t are assumed to be mutually uncorrelated at all leads and lags.

The model is estimated using Bayesian methods. The prior densities are set by following Primiceri (2005). Details are reported in the appendix. Time variation is controlled for by setting a prior model in which the standard deviation of a parameter's innovation is assumed to be a given percentage λ of the standard deviation of the coefficients estimated by maximum likelihood using a presample including the first 10 years of data (1975–84). In order to study the effects of parameter instabilities, I will work with two prior models: (1) a prior of moderate time variation ($\lambda = 10\%$) and (2) a prior of substantial time variation ($\lambda = 50\%$).

Figures 3 and 4 report the posterior mode of the autoregressive coefficients $\hat{A}_{1,t}$ and the 68% coverage intervals. When the prior allows for moderate time variation, the estimated coefficients do not vary substantially along the sample. Significant time variations are found when more substantial time variation is allowed. The estimated coefficients are most of the time significantly different from zero, indicating that there are significant dynamic linkages between the exchange rate and relative prices.

I draw 1,000 times the model parameters from their posterior density. For each parameter's draw I simulate the path of the real exchange rate and relative prices. Using the simulated data, I perform an out-of-sample forecasting evaluation by mimicking the out-of-sample real-time forecasting exercise performed in the previous section.

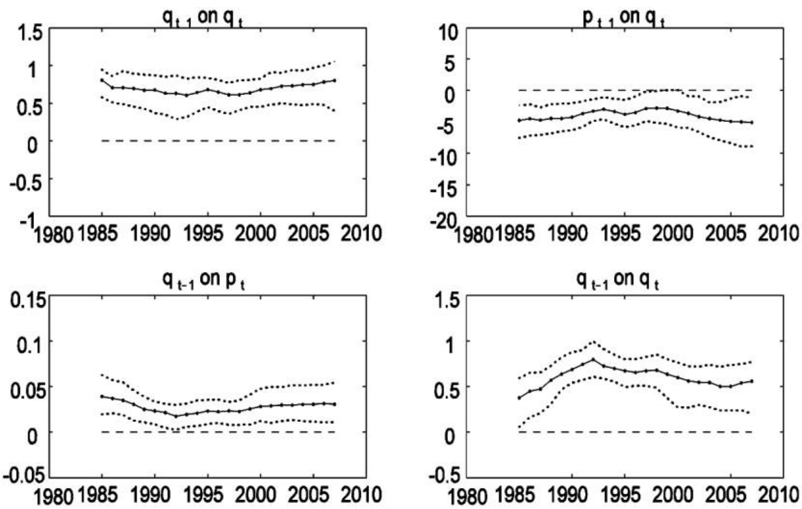

Fig. 3. The estimated time-varying coefficients (λ = 10%)

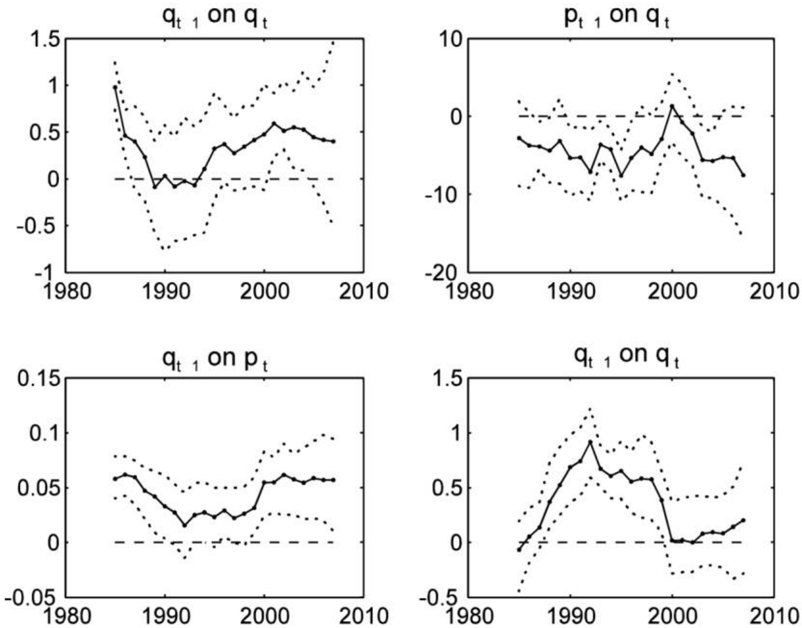

Fig. 4. The estimated time-varying coefficients (λ = 50%)

Let us consider first results when simulating the data from the model estimated using a prior of moderate time variation as reported in figure 5. I report the median, the 16th, and 84th percentiles, across simulations, of the relative mean squared forecast error. The relative mean square forecast error obtained on actual data is reported for comparison. It is evident that moderate time variation has some difficulties in replicating the pattern of the relative mean square forecast error obtained when using actual data. The simulation model cannot account for the U shape since with simulated data forecast accuracy monotonically improves when the estimation sample become longer. For short and long estimation windows the relative mean square error obtained using actual data is at the boundary of the bands, indicating that the model implies a higher predictability than the one observed in the data. A similar pattern is obtained when the simulation is based on the model with fixed, instead of moderately time-varying, coefficients.

The features of the data are better captured when we simulate the data from the model estimated using a prior that allows for a substantial amount of parameter instabilities (fig. 6). In particular, the mean square forecast error is now well in the middle of the bands. The simulated model is also able to partially reproduce the deterioration of forecasting accuracy

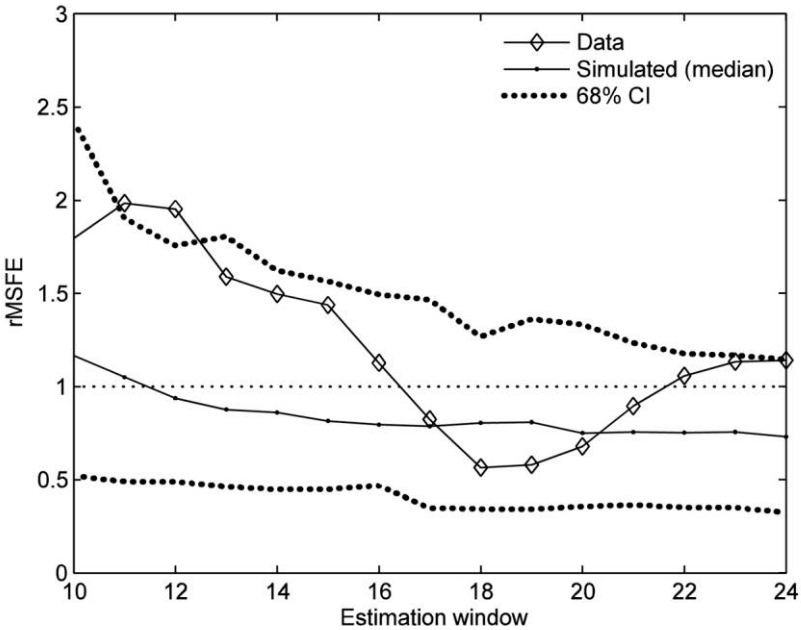

Fig. 5. The relative mean square forecast error: actual data and data simulated from the time-varying model estimated using a prior of moderate time variation ($\lambda = 1/10$).

for large estimation samples. In a comparison of figure 5 and figure 6, it is evident that the out-of-sample forecasting accuracy deteriorates when data are generated by more substantial time variation. This is in contrast with Bacchetta et al.'s claim that persistent time variation improves forecast accuracy.

In summary, results point out that estimation uncertainty alone cannot explain the pattern of forecast accuracy in the actual data. To match the data, a substantial amount of time variation is needed.

IV. Conclusions

In this discussion I have proposed an empirical exercise alternative to that presented by Bacchetta et al. in which I consider permanent rather than temporal structural change. Contrary to what is found by the authors, I find some predictability for the euro/dollar exchange rate using relative prices as fundamentals. Parameter instability and estimation uncertainty are both relevant since the accuracy of exchange rate forecasts tends to deteriorate when the estimation sample becomes too large. In addition, only when allowing for substantial parameter instability is

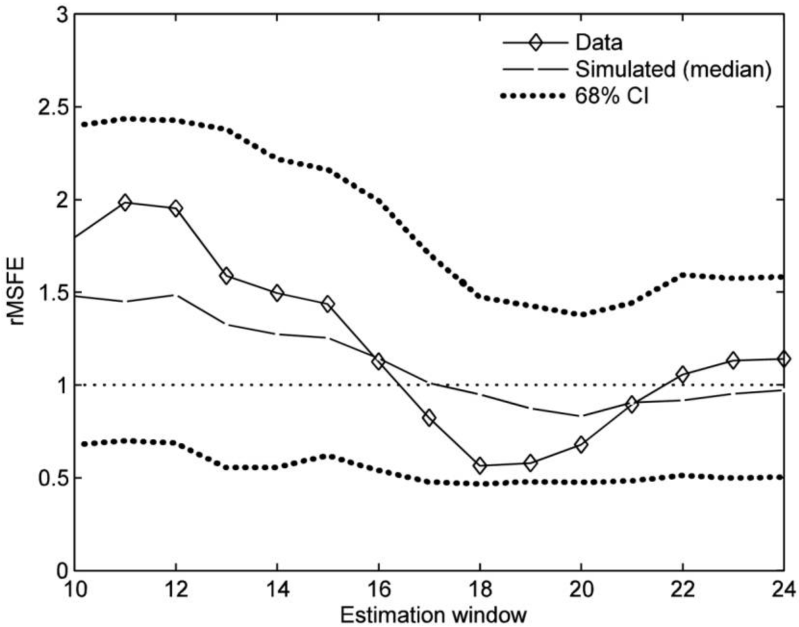

Fig. 6. The relative mean square forecast error: actual data and data simulated from the time-varying model estimated using a prior of substantial time variation ($\lambda = 1/2$).

it possible to match the patterns of forecast accuracy found in actual data.

These features have been overlooked by Bacchetta et al. since their simulation exercise has not been properly designed for investigating long-lasting structural changes and does not take into account dynamic linkages over the medium to long term, the horizon at which fundamentals are expected to play a more relevant role in exchange rate determination.

The exercise performed in this discussion is rather stylized, and a number of issues are still open. Using the time-varying VAR model for forecasting is an interesting and promising route for improving the accuracy of exchange rate predictions.

Appendix

The model setting and the estimation are accurately described in Primiceri (2005). This appendix briefly describes the specification of our priors. First, the coefficients of the covariances of the log volatilities and the hyperparameters are assumed to be independent of each other. The priors for the initial states θ_0 of the time-varying coefficients, simultaneous relations

ϕ_0, and log standard errors log σ are assumed to be normally distributed. The priors for the hyperparameters Ω, Ξ, and Ψ are assumed to be distributed as independent inverse-Wishart. More precisely, the priors are as follows:

- time-varying coefficients: $P(\theta_0) = N(\hat{\theta}, \hat{V}_\theta)$ and $P(\Omega) = IW(\Omega_0^{-1}, \rho_1)$,
- stochastic volatilities: $P(\log \sigma_0) = N(\log \hat{\sigma}, I_n)$ and $P(\Psi_i) = IW(\Psi_{0i}^{-1}, \rho_{3i})$,
- simultaneous relations: $P(\phi_{i0}) = N(\hat{\phi}_i, \hat{V}_{\phi_i})$ and $P(\Xi) = IW(\Xi_0^{-1}, \rho_2)$,

where the scale matrices are parameterized as follows: $\Omega_0^{-1} = \lambda_1 \rho_1 \hat{V}_\theta$, $\Psi_{0i} = \lambda_{3i} \rho_{3i} \hat{V}_{\phi_i}$, and $\Xi_0 = \lambda_2 \rho_2 I_n$. The hyperparameters are calibrated using a time-invariant recursive VAR estimated using a presample consisting of the first 10 years of data (1975–84). For the initial states θ_0 and the contemporaneous relations ϕ_{i0}, the means, $\hat{\theta}$ and $\hat{\phi}_i$, and the variances, $\hat{V}_\theta$ and $\hat{V}_{\phi_i}$, are set to be the maximum likelihood point estimates and four times its variance. For the initial states of the log volatilities, log σ_0, the mean of the distribution is chosen to be the logarithm of the point estimates of the standard errors of the residuals of the estimated time-invariant VAR. The degrees of freedom for the covariance matrix of the drifting coefficient's innovations are set to be equal to 10, the size of the presample. The degrees of freedom for the priors on the covariance of the stochastic volatilities' innovations are set to be equal to the minimum necessary for ensuring that the prior is proper. In particular, ρ_1 and ρ_2 are equal to the number of rows Ξ_0^{-1} and Ψ_{0i}^{-1} plus one, respectively. The parameters λ_i are very important since they control the degree of time variations in the unobserved states. The smaller such parameters are, the smoother and smaller the changes in coefficients. The results reported in the paper are obtained by setting (*a*) $\lambda_1 = 1/10^2$, $\lambda_2 = 1/10$, and $\lambda_3 = 1/10^2$ in the prior with moderate time variation ($\lambda = 1/10$) and (*b*) $\lambda_1 = 1/2^2$, $\lambda_2 = 1/2$, and $\lambda_3 = 1/2^2$ for the prior with substantial time variation ($\lambda = 1/2$).

Endnotes

1. Qualitative results are confirmed when looking at unconditional predictions.
2. These results are in line with those of Molodtsova and Papell (2009), who also find some evidence of exchange rate predictability using a wider range of models and countries.

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