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Structural breaks in Taylor rule based exchange rate models — Evidence from threshold time varying parameter models

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HIGHLIGHTS

- A recent econometric methodology is applied to eleven currencies vis-à-vis the US dollar.
- The model yields more precise density predictions for all currencies under consideration.
- During the recent financial crisis our framework delivers accurate predictions.
- We find pronounced accuracy gains during the recent period of the zero lower bound.

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ABSTRACT

In this note we develop a Taylor rule based empirical exchange rate model for eleven major currencies that endogenously determines the number of structural breaks in the coefficients. Using a constant parameter specification and a standard time-varying parameter model as competitors reveals that our flexible modeling framework yields more precise density forecasts for all major currencies under scrutiny over the last 24 years.

1. Introduction

Since the seminal contribution of Meese and Rogoff (1983) showed that empirical exchange rate models fail to outperform simple random walk specifications, a plethora of literature aimed to improve the predictive capabilities of empirical exchange rate models (see the discussion in Rossi, 2013). Recently, Molodtsova and Papell (2009) provide some evidence that Taylor rule based exchange rate models outperform other structural models in terms of out-of-sample predictive performance. However, this branch of the literature typically assumes constant coefficients in the exchange rate equation, effectively imposing strong restrictions on the underlying causal relationships (some exceptions are Canova, 1993; Abbate and Marcellino, 2014; Byrne et al., 2016; Huber, 2016). Evidence on time-varying Taylor rules (Byrne et al., 2016) suggests that it pays off to allow for time-variation in the underlying structural parameters.

In this note, we apply a recent econometric methodology put forward in Huber et al. (2016) to a set of eleven exchange rate pairs and assess whether using a threshold time-varying parameter model (TTVP) improves the out-of-sample predictive performance. Our model is benchmarked against a standard time-varying parameter model with stochastic volatility (TVP-SV) and a constant parameter model.

2. A flexible empirical framework to model exchange rates

We apply our modeling framework to the exchange rate of eleven economies relative to the US dollar, namely the United Kingdom, Japan, Canada, Australia, Germany, Italy, Netherlands, France, Denmark, Sweden and Switzerland. Following Molodtsova et al. (2008, 2011) and Molodtsova and Papell (2009), we assume that both countries' monetary policy reaction function is described

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by a (symmetric) Taylor rule, leading to the following exchange rate equation between the home and the foreign country f

$$\Delta s_t = \beta_0 - \beta_\pi^{US}\pi_t + \beta_\pi^f \tilde{\pi}_t + \gamma_u^{US} u_t - \gamma_u^f \tilde{u}_t - \kappa_i^{US} i_{t-1} + \kappa_i^f \tilde{i}_{t-1} + \varepsilon_t. \quad (2.1)$$

Here we let $\Delta s_t (t = 1983 : M01, \ldots, T = 2014 : M12)$ denote the monthly change in the nominal exchange rate measured as the price of country fth currency in terms of the home currency and $\sim$ marks foreign variables. Thus $\Delta s_t > 0$ implies an depreciation of the US dollar. Furthermore π_t denotes month-on-month CPI inflation and u_t denotes the civilian unemployment rate to measure the output gap.[1] Moreover we let i_t denote the three-month money market rate. For the Euro Area countries, we link the exchange rate series with the EUR/USD exchange rate after the Euro has been introduced. Finally, $\varepsilon_t \sim \mathcal{N}(0, \sigma_j^2)$ is a white noise process with constant variance σ_j^2.

The corresponding regression coefficients $\boldsymbol{\beta} = (\beta_0, -\beta_\pi^{US}, \beta_\pi^f, \gamma_u^{US}, -\gamma_u^f, -\kappa_i^{US}, \kappa_i^f)'$ and the error variances σ_j^2 are typically assumed to be constant over time. In this note we assess whether it improves predictive abilities if we allow for movements in the parameters of Eq. (2.1). More specifically, we estimate the following model,

$$\Delta s_t = \boldsymbol{X}_t' \boldsymbol{\beta}_t + \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0, e^{h_t}), \quad (2.2)$$

with $\boldsymbol{X}_t$ being a stacked vector of data. To closely mimic the information set available to the forecaster at time t we assume that macroeconomic variables are available only with a one-period lag while short-term interest rates are available in real-time.

Each element of $\boldsymbol{\beta}_t$, β_{kt} $(k = 1, \ldots, 7)$, evolves as

$$\beta_{kt} = \beta_{kt-1} + d_{kt}\vartheta_k \eta_{kt}, \quad (2.3)$$

where $\eta_{kt} \sim \mathcal{N}(0, 1)$ and ϑ_k^2 denotes the error variance of the latent states. Moreover, d_{kt} denotes the indicator function that equals unity if the absolute change in β_{kt}, $|\Delta\beta_{kt}|$ is large enough, i.e. exceeds a certain threshold c_k. This implies that if $|\Delta\beta_{kt}| < c_k$, $d_{kt} = 0$ and $\beta_{kt} = \beta_{kt-1}$, meaning that the jth coefficient is kept constant from $t-1$ to t. Finally, we let h_t denote the log-volatility that evolves according to a first-order autoregressive process (see Kastner and Frühwirth-Schnatter, 2014).

This modeling approach has been introduced in Huber et al. (2016) to search for appropriate model specifications over time. As compared to a standard time-varying parameter model that sets $d_{kt} = 1$ for all k, t, our model allows to discriminate between periods where parameters have been moving significantly over time or periods where parameters remained relatively constant. While a standard TVP model imposes the restriction that parameters evolve smoothly over time, our threshold TVP model is capable of accommodating large swings in the respective parameters. Moreover, our model is also able to detect cases where elements of β_t display only a relatively low number of structural breaks. In addition, through Bayesian shrinkage priors, our model also investigates whether certain parameters in Eq. (2.1) should be set equal to zero. This captures the notion that some central banks do not react to movements in the output gap (i.e. $\beta_u^f = 0$) or perform interest rate smoothing (i.e. $\beta_i^f = 0$).[2]

Our model thus endogenously detects whether we need a model with a low, moderate or a large number of structural breaks. Especially for Taylor rule based models, the question whether the monetary policy reaction function of a given central bank remained constant over time is questionable. For instance, it could be the case that the central bank does not change its stance towards inflationary developments over time but aggressively targets the output gap during crisis periods. The proposed model is capable of detecting such regime shifts in a data-based fashion.

3. Forecasting results

In this section we perform a forecasting horse race using three models. The first one is a constant parameter model given by Eq. (2.1). The second specification is the threshold TVP (TTVP) model and the final model adopted is a standard TVP model (i.e. $d_{kt} = 1$ for all k, t).

We estimate all models using Bayesian methods. The prior specification and the corresponding Markov chain Monte Carlo algorithm adopted for all models is described in more detail in Huber et al. (2016). For the constant parameter model we use relatively uninformative priors on the regression coefficients and an inverted Gamma prior on σ_j^2 with scale and shape parameter equal to 0.01.

Our forecasting design relies on rolling window estimation. We use the period ranging from 1983:M01 to 1994:M01 (132 observations) as an initial estimation sample and the remaining 352 (24 years) observations as an hold-out sample. We compute the one-step-ahead predictive density for each point in our hold-out sample and consequently move the estimation sample by a single observation forward while dropping the first observation. This provides us with a sequence of 352 predictive densities, a comparatively large hold-out sample. Because previous studies devoted most attention to point forecasts, we focus mainly on the log predictive score, a typical Bayesian criterion to evaluate model predictions (see Geweke and Amisano, 2010, for a discussion on the log predictive likelihood). Moreover, we also briefly assess the out-of-sample fit by investigating the evolution of the cumulative squared forecast errors.

Fig. 1 depicts the evolution of the log predictive score (LPS, left panel) and the cumulative squared forecast errors (right panel) over the hold-out sample for all countries under consideration.

The figure reveals that for all eleven currencies, the TTVP model outperforms both, a constant parameter model (indicated by positive values of the relative LPS) and the TVP model. The results for the TVP model suggest that for the United Kingdom and Canada, the simple linear regression model outperforms the more flexible time-varying parameter model. This result can be traced back to the fact that we rely on a rolling window forecasting design that keeps the number of observation used in the estimation fixed. A heavily parameterized model like the TVP specification features a high dimensional state vector, implying that the number of parameters to be inferred is large relative to the number of available observations, leading to overfitting issues.[3] Visual inspection of the corresponding predictive densities (not shown) corroborates these findings. Taken at face value our results indicate that the amount of shrinkage on the time-variation *and* the initial state supplied by the TTVP framework alleviates overfitting problems effectively, providing a parsimonious model that is useful for a large battery of exchange rates.

The steep increase in predictive accuracy, as measured by the LPS, during and after the global financial crisis may be attributed to two distinct sources. The first source is that most central banks in developed economies aggressively lowered interest rates, reaching the zero lower bound (ZLB) within one year after the

1 We have experimented with (detrended) industrial production to measure real activity. The results appear to be relatively similar.

2 For more information how this is accomplished, see Huber et al. (2016).

3 In fact, using a recursive forecasting design shows that the performance differences between the TTVP and the TVP model become somewhat smaller towards the second half of the hold-out sample.