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Exchange Rates and Macroeconomic Fundamentals: Evidence of Instabilities from Time-Varying Factor Loadings

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Summary

We examine the relationship between exchange rates and macroeconomic fundamentals using a two-step maximum likelihood estimator through which we compute time-varying factor loadings. Factors are obtained as principal components, extracted from a large macro-dataset. Using 14 currencies over 1995–2018, we show that the loadings on the factors vary considerably over time with frequent sign changes. Allowing for time-varying loadings increases the percentage of explained variation in exchange rates by an order of magnitude. Accounting for instabilities improves the predictive ability of the model globally and locally during crises, and yields better forecast of sign changes in exchange rates.

JEL Classification Numbers: C32; C38; C51, C52; C53; C55; F31.

Keywords: foreign exchange rates; macroeconomic factors; time-varying loadings; high-dimensional factor models; exchange rate forecasting;

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1 Introduction

In this paper, we study the unstable relationship between exchange rates and macroeconomic fundamentals. Using a model that relates foreign exchange rates with macroeconomic factors, we show that allowing for time-varying loadings can increase the percentage of explained variation in exchange rates by an order of magnitude. In addition, taking the aforementioned instabilities into consideration improves the relative out-of-sample predictive ability of the model globally, and yields better forecast of sign changes in exchange rates.

It is intuitively plausible that countries' exchange rates are related to their underlying macroeconomic fundamentals. Indeed, theoretical models based on money demand functions or monetary policy rules suggest fundamentals offer explanatory power (see [Engel and West, 2005](#), for a survey of such models). Nevertheless, the form and existence of such a relationship is contentious. Since [Meese and Rogoff's \(1983a\)](#) key finding that structural exchange rate models perform no better than a random walk, arduous research work has been invested into this *disconnect puzzle* ([Obstfeld and Rogoff, 2000](#)); however, often to no avail ([Rossi, 2013](#)). Crucially, any empirical investigation must be based on a theoretical model that adequately captures the structural link to fundamentals. Survey evidence of UK and US based foreign exchange (FX) traders finds that the weight they attach to macroeconomic variables changes over time ([Cheung and Chinn, 2001](#); [Cheung et al., 2004](#)). This reflects an early hypothesis of [Meese and Rogoff \(1983a,b, 1988\)](#) that time-varying parameters could be a reason behind the poor performance of structural models.¹

The exchange rate model in this paper is also related to the scapegoat theory ([Bacchetta and van Wincoop, 2004, 2012, 2013](#)). A scapegoat effect arises if there is uncertainty about the structural parameters governing the exchange rate equation. It is the expectation of these parameters that then determines the exchange rate. An observed fundamental becomes a scapegoat as a result of an unobserved shock with which it is correlated, in which case investors rationally attribute the observed exchange rate fluctuations to that specific fundamental. The expectation of the respective parameter rises temporarily, meaning the fundamentals receive time-varying weights. [Fratzscher et al. \(2015\)](#) are the first to present empirical support for this theory by examining a survey of FX traders to obtain a measure of the scapegoat weights. Consistent with [Bacchetta and van Wincoop \(2004, 2013\)](#), they find fundamentals that are temporarily deviating from their long-term equilibrium to be chosen as scapegoats. In the same vein, [Pozzi and Sadaba \(2020\)](#) construct parameter expectations from survey data and use a Bayesian approach to determine the probability that variables are scapegoats. They find inflation rates to be the most likely scapegoat candidate. A slightly different explanation for the disconnect puzzle is offered by [Bacchetta and van Wincoop \(2006\)](#) who model the relation of the exchange rate and order flows. In the short-run, the exchange rate is mainly driven by unobserved trades. Heterogeneously informed investors cannot disentangle whether variations are caused by order flows or private signals about fundamentals. [Bacchetta and van Wincoop's \(2006\)](#) model suggests fundamentals only have explanatory power over long horizons while trades matter in the short-run. It is empirically corroborated by [Rime et al. \(2010\)](#), who show that order

¹Although several studies indicate such constant parameter models fail to predict exchange rates (e.g. [Cheung et al., 2005](#); [Rossi, 2013](#)) there are others that find support for them (e.g. [Li et al., 2015](#); [Molodtsova and Papell, 2009](#))

flow aggregates information about fundamentals and can forecast exchange rate changes. [Cao et al. \(2019\)](#) take a different approach and analyse the term structure of exchange rates by decomposing them into carry-trade risk-premia and forward premium components. They find customer order flows to be informative about the former, although a quarter of order-flow variation is driven by scapegoat variables. Both studies demonstrate the importance of time-variation in exchange rate models. The disconnect puzzle may, however, also be a product of inaccurate model selection, as suggested by [Sarno and Valente \(2009\)](#): models would have to be altered frequently to optimally capture the information embedded in fundamentals and this implies a high degree of time-variation in their parameters. [Kouwenberg et al. \(2017\)](#) develop a dynamic model selection rule which they find to produce better forecasts than several benchmark models. The reason behind this lies, again, in the rule's ability to incorporate time-variation. Further evidence for parameter instability in exchange rate regressions is provided by [Rossi \(2006\)](#), [Bekiros \(2014\)](#), and [Byrne et al. \(2018\)](#).² We demonstrate how a time-varying relationship is theoretically consistent with – but not exclusively dependent on – scapegoat effects and presents extensive empirical evidence for such instabilities.

In this paper, we specify a theoretical model in which exchange rate changes are described by a stochastic difference equation that consists of a linear combination of observable and unobservable fundamentals. The latter can be interpreted as transitory shocks that shift the weight investors attribute to a particular fundamental away from its long-run equilibrium. These structural instabilities manifest themselves in a time-varying derivative of exchange rate changes with respect to observable fundamentals, that we write in state space form and estimate using the theoretical results of [Mikkelsen et al. \(2019\)](#) who show that consistent estimates of the time-varying loadings can be obtained by maximising the likelihood function of the model.³ To extract the factors serving as fundamentals, we use the [McCracken and Ng \(2016\)](#) database of US macro-variables and merge it with a dataset of 171 macro series, compiled from the OECD database, yielding a novel dataset of 290 time series spanning from 1994:12 to 2018:12. The information inherent in these series is extracted via principal components. The model is tested for 14 different currencies *vis-à-vis* the US dollar and compared to a benchmark model with constant loadings. The paper provides in-sample evidence that accounting for time-variation improves the model fit considerably as demonstrated by an R^2 ranging from 37% up to 88%. It correctly matches an appreciation and depreciation up to 86% of the times, whereas the constant loadings model can only explain a very small part of exchange rate variations, demonstrated by an R^2 between 1% and 14%. We expound how the time-varying loadings estimates can be interpreted economically and how they may capture the effects of fundamentals during currency crises or on safe haven currencies. In addition, we show that taking the aforementioned instabilities into consideration

²While most studies indicate that the link between exchange rates and fundamentals is unstable, [Balke et al. \(2013\)](#) suggest the poor performance of constant parameter models is due to the relevant signals entailed in fundamentals being obscured by noise.

³Several papers have been proposed recently to estimate time variations in large dimensional factor models. Examples besides [Mikkelsen et al. \(2019\)](#) two-step maximum likelihood estimator are: [Breitung and Eickmeier \(2011\)](#) propose a Chow-type tests for structural breaks in factor models that is asymptotically unaffected by the estimation error of the principal components; [Su and Wang \(2017\)](#) consider a local principal component estimator for latent factors and smoothly changing time-varying factor loadings; [Barigozzi et al. \(2020\)](#) introduce a generalised dynamic factor model, in which factors are loaded with a time-varying filter; [Barigozzi et al. \(2018\)](#) propose a method to estimate high-dimensional factor models with multiple (large) change points.

improves the relative out-of-sample predictive ability of the model globally, and yields better forecasts of sign changes in exchange rates. Furthermore, it can improve forecasts locally during crises.

The paper is structured as follows: [Section 2](#) presents the theoretical model of structural instabilities between exchange rates and fundamentals. It also illustrates the relation of the model to the scapegoat theory. In [Section 3](#), the model is mapped into state space form, and the econometric approach is described. [Section 4](#) discusses the data, and in [Section 5](#) we report the in-sample results, explore the role of parameter instabilities, and finally present the out-of-sample forecast results. [Section 6](#) concludes.

2 A Structural Model of Exchange Rate Instability

This section derives a model that explains how unobservable variables can lead to structural instabilities in the relationship of exchange rates and macroeconomic fundamentals. The model belongs to the same class as the ones examined by [Engel and West \(2005\)](#) and is derived from three basic assumptions. We elaborate on the relation of the model to the scapegoat theory of exchange rates ([Bacchetta and van Wincoop, 2004, 2012, 2013](#)).

2.1 Theoretical Framework

To introduce the theoretical framework, we specify an uncovered interest parity (UIP) condition:⁴

$$\mathbb{E}[s_{t+1}|I_t] - s_t = i_t - i_t^* + \phi_t, \quad (1)$$

where s_t is the log exchange rate measured as the domestic price per unit of foreign currency and i_t is the nominal one-period interest rate. An asterisk denotes foreign variables. The period t information set is denoted by I_t , and deviations from UIP are accounted for by the risk premium ϕ_t . In addition, Relative Purchasing Power Parity (PPP) is assumed:

$$\Delta s_t = \pi_t - \pi_t^* = \frac{1}{\mu} \mathbb{E}[\pi_{t+1} - \pi_{t+1}^* | I_t], \quad (2)$$

with inflation being defined as the change in log price levels $\pi_t = p_t - p_{t-1}$. $\mu > 1$ is the discount factor in the economy. Finally, we use the following relationship of real interest rates and macroeconomic fundamentals:

$$r_t - r_t^* = -f_t'(\beta + \kappa_t), \quad (3)$$

where $r_t = i_t - \mathbb{E}[\pi_{t+1}|I_t]$ is the *ex ante* real interest rate. This equation states that the spread between foreign and domestic real interest rates is negatively related to changes in observed and unobserved macroeconomic fundamentals. The parameter vector β reflects the long-run equilibrium relationship between observable fundamentals f_t and real interest rates. It implies that there is a constant long-run

⁴See [Engel \(2014\)](#) for a survey of exchange rates and interest parity as well as the existence of the risk premium term.

equilibrium between the two. However, in the short-run, stationary, mean-zero, unobserved shocks, described by the vector $\kappa_t = (\kappa_{1t}, \dots, \kappa_{rt})$, disequilibrate real interest rates and fundamentals. Such shocks can represent shifts in parameter expectations but also changing expectations about future fundamentals, e.g. caused by macroeconomic news. One interpretation of (3) is that it reflects the real interest rate channel of monetary policy, an intrinsic feature of New-Keynesian models. Due to nominal rigidities, changes in the nominal interest rate (and other policy instruments) lead to shifts in real interest rates that bring about fluctuations in economic variables.⁵ To illustrate that (3) not only relates to the macroeconomic literature more broadly but also encompasses specific models, we show in [Appendix A.1](#) how this equation can be derived from a Taylor rule model which restricts the specific variables included in $f_t = (f_{1t}, \dots, f_{rt})$.⁶ After substituting (2) into (3), one obtains an equation similar to the one in [Bacchetta and van Wincoop \(2013\)](#):⁷

$$i_t - i_t^* = \mu \Delta s_t - f'_t(\beta + \kappa_t).$$

Combining this result with (1) leads to:

$$\begin{aligned} \mathbb{E}[\Delta s_{t+1}|I_t] &= \mu \Delta s_t - f'_t(\beta + \kappa_t) + \phi_t \\ \Delta s_t &= \frac{1}{\mu} \{f'_t(\beta + \kappa_t) - \phi_t + \mathbb{E}[\Delta s_{t+1}|I_t]\}. \end{aligned}$$

Recursive substitution of Δs_t , assuming no bubbles, yields a single stochastic difference equation:

$$\Delta s_t = \frac{1}{\mu} \left\{ \sum_{j=0}^{\infty} \left(\frac{1}{\mu}\right)^j \mathbb{E}[f'_{t+j}(\beta + \kappa_{t+j})|I_t] - \sum_{j=0}^{\infty} \left(\frac{1}{\mu}\right)^j \mathbb{E}[\phi_{t+j}|I_t] \right\}, \quad (4)$$

establishing the common result that the exchange rate equals the present value of expected future macroeconomic fundamentals and the foreign exchange risk premium. Recall that κ_t are transitory shocks of potentially differing origins. Two examples are large unobserved liquidity trades or the anticipation of a dampened economic outlook that has not yet manifested itself in observable data. In any case, (4) implies incomplete parameter information on the effect of fundamentals. Consequently, the relative importance of fundamentals in determining the exchange rate is not time-invariant and affected by κ_t . To derive the effect of changes in observed fundamentals on the exchange rate, consider for simplicity the case of a single fundamental and assume that f_t , κ_t , and ϕ_t follow AR(1) processes:

$$\begin{aligned} f_t &= \rho_f f_{t-1} + v_t, & v_t &\sim i.i.d.(0, \sigma_f^2) \\ \kappa_t &= \rho_\kappa \kappa_{t-1} + u_t, & u_t &\sim i.i.d.(0, \sigma_\kappa^2) \\ \phi_t &= \rho_\phi \phi_{t-1} + w_t, & w_t &\sim i.i.d.(0, \sigma_\phi^2), \end{aligned} \quad (5)$$

⁵This channel is covered by standard textbooks, such as [Galí \(2015\)](#).

⁶Imposing such restrictions introduces additional model uncertainty and resulting expressions have been tested by the literature *in extenso*, often with limited success (e.g. [Rossi, 2013](#)).

⁷[Bacchetta et al. \(2010\)](#) derive the expression $i_t - i_t^* = \mu \Delta s_t - \mu \Delta(F_t + b_t)$ from the monetary model of the exchange rate, where b_t are unobservable fundamentals and $F_t = f_t \beta$.

where $|\rho_f|, |\rho_\kappa|, |\rho_\phi| < 1$. Clearly, $\mathbb{E}[f_{t+j}|I_t] = \rho_f^j f_t$ and $\mathbb{E}[\kappa_{t+j}|I_t] = \rho_\kappa^j \kappa_t$. Assuming f_t and κ_t are uncorrelated, (4) becomes:

$$\begin{aligned}\Delta s_t &= \frac{1}{\mu} \sum_{j=0}^{\infty} \left(\frac{1}{\mu}\right)^j \rho_f^j f_t \beta + \frac{1}{\mu} \sum_{j=0}^{\infty} \left(\frac{1}{\mu}\right)^j \rho_\kappa^j f_t \kappa_t - \frac{1}{\mu} \sum_{j=0}^{\infty} \left(\frac{1}{\mu}\right)^j \rho_\phi^j \phi_t \\ &= f_t \left(\frac{1}{\mu - \rho_f} \beta + \frac{1}{\mu - \rho_\kappa} \kappa_t \right) - \frac{1}{\mu - \rho_\phi} \phi_t.\end{aligned}\tag{6}$$

The derivative of the exchange rate with respect to the observed fundamentals is:

$$\frac{\partial \Delta s_t}{\partial f_t} = \left(\frac{1}{\mu - \rho_f} \beta + \frac{1}{\mu - \rho_\kappa} \kappa_t \right).\tag{7}$$

That is, the effect of variations in macroeconomic fundamentals on the exchange rate corresponds to a constant part, $\frac{1}{\mu - \rho_f} \beta$, and a time-varying part, $\frac{1}{\mu - \rho_\kappa} \kappa_t$. It can be seen that the presence of unobservable fundamentals leads to an unstable relationship between observed fundamentals and the exchange rate. Based on studies of equations similar to (4), one can expect that μ is close to one (Engel and West, 2005). In that case, if the transitory shocks are highly persistent relative to the observable fundamentals, the relationship between the latter and exchange rates is characterised by a greater degree of instability.

2.2 Relation to the Scapegoat Theory

The model relates to Bacchetta and van Wincoop's (2013) scapegoat theory in the sense that they also consider a model based on a single stochastic difference equation like (4). In their framework, fundamentals, too, display temporary changes in their weights; however, this is the result of investors being unable to pin down the value of the structural parameters in β . If parameters were known, their model simply implies $\frac{\partial s_t}{\partial f_{i,t}} = \beta_i$. If parameters are unknown, on the other hand, agents form their expectations of β over time by updating their beliefs about the impact of fundamentals which takes the form $f_t' \beta + b_t$. Here, b_t are unobserved shocks that coincide with changes in fundamentals and thus introduce time-variation. Investors can observe a large value of the signal $f_t' \beta + b_t$ but are unable to distinguish whether this is due to β being greater than expected or a result of changes in the unobservables b_t . It becomes rational for agents to attribute at least some weight to a larger β , thereby raising their expectations of the structural parameters. Consequently, the relationship between fundamentals and the exchange rate becomes time-varying, in spite of the structural parameters being constant. This manifests itself in the derivative of the exchange rate with respect to fundamentals:

$$\frac{\partial s_t}{\partial f_{i,t}} = \theta \beta_i + (1 - \theta) \mathbb{E}[\beta_i | I_t] + (1 - \theta) f_t' \frac{\partial \mathbb{E}[\beta | I_t]}{\partial f_{i,t}},$$

where the first two terms on the right-hand side are a weighted average of the true structural parameters and their expectations. The time-varying last term reflects the gradual learning about β . In Bacchetta and van Wincoop (2013), unobserved fundamentals can i.a. reflect macroeconomic

news.⁸ However, while trying to explain the arising fluctuations rationally, heterogeneously informed investors attribute these shocks to an observable fundamental which temporarily receives an excessive weight as a result.⁹ Therefore, the [Bacchetta and van Wincoop \(2013\)](#) model leads to similar relationship between fundamentals and the exchange rate as the model in this paper.

3 Modelling Parameter Instability

3.1 State Space Formulation

This subsection demonstrates how the theoretical model can be mapped into state space form. Focus on the single factor case for illustrative purposes and combine (6) with the autoregressive processes for the unobservable shocks to obtain the system:

$$\begin{aligned}\kappa_t &= \rho_\kappa \kappa_{t-1} + u_t, \\ \Delta s_t &= f_t \left(\frac{1}{\mu - \rho_f} \beta + \frac{1}{\mu - \rho_\kappa} \kappa_t \right) - \frac{1}{\mu - \rho_\kappa} \phi_t.\end{aligned}\tag{8}$$

To estimate the relation of exchange rates to fundamentals, $\frac{1}{\mu - \rho_f} \beta + \frac{1}{\mu - \rho_\kappa} \kappa_t$, write the system in the following state space representation:

$$\begin{aligned}\lambda_t - \bar{\lambda} &= b(\lambda_{t-1} - \bar{\lambda}) + \eta_t, & \eta_t &\sim i.i.d.(0, \sigma_\eta^2), \\ \Delta s_t &= f'_t \lambda_t + \epsilon_t, & \epsilon_t &\sim i.i.d.(0, \sigma_\epsilon^2),\end{aligned}\tag{9}$$

where the measurement error ϵ_t is an estimate of the risk premium,¹⁰ and the state vector λ_t estimates the relation between macroeconomic fundamentals f_t and the exchange rate s_t . By comparing (8) and (9), it can be seen that $\lambda_t = \frac{1}{\mu - \rho_f} \beta + \frac{1}{\mu - \rho_\kappa} \kappa_t$; hence, the parameters of the state space representation (9) can be mapped to the parameters in (8):

$$\begin{aligned}\bar{\lambda} &= \mathbb{E}[\lambda_t] = \mathbb{E} \left[\frac{1}{\mu - \rho_f} \beta + \frac{1}{\mu - \rho_\kappa} \kappa_t \right] = \frac{1}{\mu - \rho_f} \beta, \\ \frac{\sigma_\eta^2}{1 - b^2} &= \mathbb{V}[\lambda_t] = \mathbb{V} \left[\frac{1}{\mu - \rho_f} \beta + \frac{1}{\mu - \rho_\kappa} \kappa_t \right] = \mathbb{V}[\kappa_t] = \omega^2 \frac{\sigma_u^2}{1 - \rho_\kappa^2},\end{aligned}$$

where $\omega = \frac{1}{\mu - \rho_\kappa}$. The autocorrelation parameter ρ_κ of κ_t corresponds to the autocorrelation parameter b of λ_t . Therefore, estimating state space system (9) will give estimates of the parameter vector $\frac{1}{\mu - \rho_f} \beta$ and estimates of the unobserved shock process scaled by ω . The state space representation (9) can

⁸Newly released information often coincides with other events which can obfuscate the origin of a shock.

⁹Consider the following example: On the same day new unemployment figures are released, a government official issues an unrelated statement via social media that prompts a few large traders to re-balance their portfolio. Other investors may associate the resulting fluctuations with the announced change in unemployment, leading to a higher weight being placed on the observable fundamental.

¹⁰Specifically, we have $\epsilon = -\frac{1}{\mu - \rho_\phi} \phi_t$ and $\sigma_\epsilon^2 = \frac{\sigma_\phi^2}{(\mu - \rho_\phi)^2 (1 - \rho_\phi^2)}$.

easily be generalised to the multivariate case with r observed fundamentals $f_t = (f_{1t}, \dots, f_{rt})'$ and state vector $\lambda_t = (\lambda_{1t}, \dots, \lambda_{rt})'$:

$$\begin{aligned} B(L)(\lambda_t - \bar{\lambda}) &= \eta_t, & \eta_t &\sim i.i.d.(0, Q), \\ \Delta s_t &= f_t' \lambda_t + \varepsilon_t, & \varepsilon_t &\sim i.i.d.(0, \sigma_\varepsilon^2), \end{aligned} \tag{10}$$

where $B(L) = I - B_{t,1}^0 L - \dots - B_{t,q}^0 L^q$ is a q^{th} -order lag polynomial with roots outside the unit circle. The covariance matrix of the state innovation, η_t , is $\mathbb{E}[\eta_t \eta_t'] = Q$.

3.2 A Factor Model with Time-Varying Loadings

To estimate the system (10) empirically, we specify a factor model with time-varying loadings. The effect of fundamentals on the exchange rate in the presence of structural instabilities can be identified by using two important theoretical results: (i) the principal component estimator gives consistent factor estimates even in the presence of time-varying loadings (Bates et al., 2013). (ii) Maximising the likelihood of a factor model with principal components as estimators of the unobservable factors gives consistent estimates of stationary time-varying loadings (Mikkelsen et al., 2019).

We use a large panel of macroeconomic data series $X_t = (X_{1t}, \dots, X_{Nt})'$, $t = 1, \dots, T$, whereby we assume that X_{it} has an appropriate factor structure:

$$X_{it} = \alpha_{it}' f_t + \epsilon_{it},$$

where f_t is an $r \times 1$ vector of common factors, α_{it} are the corresponding time-varying factor loadings, and ϵ_{it} are idiosyncratic errors. The appropriate factor structure allows the idiosyncratic errors to have limited cross-sectional correlation. The number of factors, r , is considerably smaller than the number of series, N , such that the information in the large number of macroeconomic variables is condensed into the r -dimensional factors. That is, by extracting the first r principal components of X_t , one can construct a set of macroeconomic indicators that represents the information contained in the observable fundamentals. The principal components estimator treats the loadings as being constant over time, i.e. $\alpha_{it} \equiv \alpha_i$, and solves the minimisation problem:

$$(\tilde{f}, \tilde{\alpha}_i) = \min_{f, \alpha_i} (NT)^{-1} \sum_{i=1}^N \sum_{t=1}^T (X_{it} - \alpha_i' f_t)^2,$$

where $\tilde{f}$ is a $T \times r$ matrix of common factors, and $\tilde{\alpha}$ is an $r \times 1$ vector of factor loadings. By concentrating out α_i and imposing the normalisation constraint $f'f/T = I_r$, the minimisation problem becomes equivalent to maximising $\text{tr}(f'(X'X)f)$, where X is the $T \times N$ matrix of observations. The resulting factor matrix is given by $\sqrt{T}$ times the eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix XX' . It follows from Bates et al.'s (2013) main result that the fundamentals in (10) can be represented through the r principal component estimates, $\tilde{f}_t$, in spite of the structural instability underlying the state vector λ_t .

Having obtained the principal component estimates, we estimate the parameters of the state space model (10) by forming the likelihood function:

$$\mathcal{L}_T(\Delta s|\tilde{f};\theta) = -\frac{1}{2}\log(2\pi) - \frac{1}{2T}\log|\Sigma| - \frac{1}{2T}(\Delta s - \mathbb{E}[\Delta s])'\Sigma^{-1}(\Delta s - \mathbb{E}[\Delta s]),$$

where $\Delta s = (\Delta s_1, \dots, \Delta s_T)'$ with mean $\mathbb{E}[\Delta s] = f\tilde{\lambda}$ and variance matrix $\mathbb{V}[\Delta s] = \Sigma$. The parameter vector $\theta = (B(L), \tilde{\lambda}, Q, \sigma_\varepsilon^2)$ is estimated as:

$$\tilde{\theta} = \arg \max_{\theta} \mathcal{L}_T(\Delta s|\tilde{f};\theta).$$

The likelihood can be computed efficiently with the Kalman filter as (10) is a linear state space system. Mikkelsen et al. (2019) show that under standard assumptions and provided $T/N^2 \rightarrow 0$, the maximum likelihood estimator is consistent for the parameters of the time-varying factor loadings λ_t , i.e. $\tilde{\theta} \xrightarrow{P} \theta$. Once $\tilde{\theta}$ is obtained, the estimates of the factor loadings $\tilde{\lambda}_t$ for $t = 1, \dots, T$ are computed with the state smoother. As emphasised in Mikkelsen et al. (2019), these estimates are consistent even under missing factors.

In addition to the time-varying model, we estimate a constant parameter benchmark in order to assess the relative contribution of time varying loadings in explaining exchange rate fluctuations. In that case, (8) reduces to $\Delta s_t = f_t \frac{1}{\mu - \rho_f} \beta - \frac{1}{\mu - \rho_k} \phi_t$, i.e. a present value model for exchange rates with constant parameters. Therefore, the reduced form relation between fundamentals and exchange rates, $\frac{1}{\mu - \rho_f}$, can simply be estimated by regressing Δs_t on the factors $\tilde{f}_t$. We denote $\frac{1}{\mu - \rho_f} \beta$ by $\tilde{\lambda}_{OLS}$. Comparing the in- and out-of sample fit of the two models determines if, indeed, the model of intertemporal instabilities fares better at explaining the relationship of exchange rates and fundamentals.

4 Data

4.1 Exchange Rate Data

We use monthly averages of the US dollar exchange rate vis-à-vis 14 currencies between 1999:12 and 2018:12. The considered exchange rates are: the Australian Dollar (AUD), the Brazilian Real (BRL), the Canadian Dollar (CAD), the Danish Krone (DKK), the Indian Rupee (INR), the Mexican Peso (MXN), the New Zealand Dollar (NZD), the Norwegian Krone (NOK), the South African Rand (ZAR), the Swedish Krona (SEK), the Swiss Franc (CHF), the British Pound (GBP), and the Euro (EUR). The data is compiled from the OECD database.¹¹ Table 1 reports summary statistics for the first difference of the 14 log exchange rates. Looking at the mean percentage changes, they are all either zero or very close to zero with standard deviations ranging from 1.8% to 4%. In terms of fluctuations, the Brazilian Real displays the largest downward movement with -24.2%, whereas the South African Rand appreciated the most over one month with 15.2%. All currencies are positively autocorrelated at one month, and, with the exception of the Japanese Yen, negatively at the second month. The

¹¹Prior to 1999, the exchange rate for the ECU is used in place of the Euro, i.e. an weighted average of the Austrian Schilling, Belgian and Luxembourg Francs, Finnish Markka, French Franc, German Mark, Irish Pound, Italian Lira, Netherlands Guilder, Portuguese Escudo, and Spanish Peseta.

Table 1. Summary Statistics Exchange Rates

Currency	Mean	Std.Dev.	Min.	Max.	$\hat{\rho}(1)$	$\hat{\rho}(2)$	$\hat{\rho}(3)$	Q_{BP}
AUD	-0.000	0.028	-0.180	0.073	0.345	-0.105	-0.011	0.001
CAD	0.000	0.018	-0.109	0.062	0.305	-0.035	-0.031	0.001
DKK	-0.000	0.023	-0.078	0.062	0.312	-0.064	-0.129	0.001
JPY	-0.000	0.026	-0.080	0.103	0.300	0.042	-0.092	0.001
MXN	-0.006	0.034	-0.321	0.088	0.125	-0.003	-0.059	0.001
NZD	0.000	0.028	-0.106	0.074	0.305	-0.054	0.047	0.001
NOK	-0.001	0.025	-0.131	0.057	0.352	-0.055	-0.068	0.001
SEK	-0.001	0.025	-0.108	0.071	0.353	-0.057	-0.082	0.001
CHF	0.001	0.024	-0.112	0.081	0.187	-0.110	-0.091	0.001
BRL	-0.005	0.040	-0.242	0.113	0.401	-0.055	-0.030	0.001
INR	-0.003	0.017	-0.066	0.061	0.298	-0.075	0.089	0.001
ZAR	-0.005	0.037	-0.190	0.152	0.294	-0.016	-0.138	0.001
GBP	-0.001	0.020	-0.097	0.059	0.236	-0.006	-0.075	0.001
EUR	-0.000	0.023	-0.078	0.062	0.309	-0.067	-0.127	0.001

Note: Sample Period: 1995:12 - 2018:12. $\hat{\rho}(m)$ denotes the autocorrelation at month m . Q_{BP} denotes the p-value of the Box-Pierce Q_{BP} test.

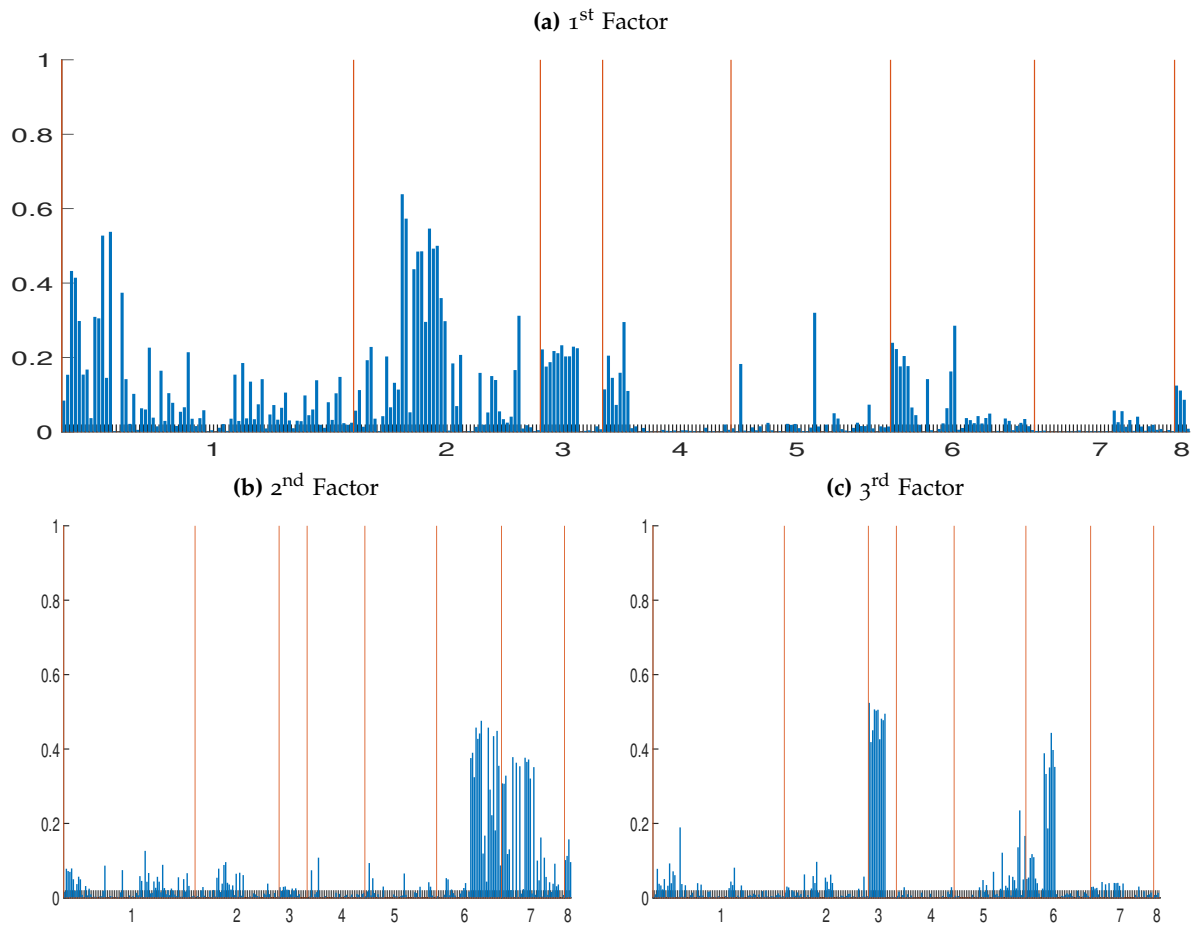
Box-Pierce test implies that, across currencies, the first three autocorrelations are all statistically significant.

4.2 Macroeconomic Fundamentals and Factors

Data – The factors are extracted from a large dataset of macroeconomic fundamentals. To this end, we combine two different data sources. First, we use [McCracken and Ng’s \(2016\)](#) FRED-MD database which contains 125 monthly time series of the US economy, categorised into: (1) Output & Income, (2) Labour Market, (3) Housing, (4) Orders & Inventories, (5) Money & Credit, (6) Interest Rates, (7) Prices, and (8) Stock Markets. Following [McCracken and Ng \(2016\)](#), 5 time series are removed to balance the panel; in addition, we remove the 5 exchange rates in the dataset to exclude them from the fundamentals. In order to ensure stationarity of all variables, we use the same transformation as [McCracken and Ng \(2016\)](#) and refer to their paper for detailed descriptions of the data and the transformations.

Second, we compile a dataset of 171 time series for the 14 remaining countries from the OECD statistical database. Specifically, we compile 21 macro-variables, the availability of which differs across countries. [Table B-1](#) summarises which variables are available for each country, how they are categorised in terms of [McCracken and Ng’s \(2016\)](#) classifications, and their original unit. Consistent with [McCracken and Ng \(2016\)](#), the variables are transformed either by taking first log-differences or first differences (see notes under [Table B-1](#)) to ensure stationarity. All series are available without missing values between 1994:12 and 2018:12, but not every series is available for all countries. That is, the dataset is balanced across time but unbalanced across countries. we combine the two datasets into a $T \times N$ matrix of $N = 290$ variables, with $T = 288$ observations each.

Figure 1. Marginal R^2 between factors and macro series



Note: R^2 from regression of each series on first, second, and third factor. Series categorised as (1) Output & Income, (2) Labour Market, (3) Housing, (4) Orders & Inventories, (5) Money & Credit, (6) Interest Rates, (7) Prices, and (8) Stock Market.

Factor Selection – In practice, the optimal number of factors describing $X_{it} = \alpha'_{it}f_t + \epsilon_{it}$ is not apparent, and multiple factor selection criteria for models where N and T are large exist. Let $V(k) = (NT)^{-1} \sum_{i=1}^N \sum_{t=1}^T (X_{it} - \tilde{\alpha}_i^{k'} \tilde{f}_t^k)^2$. While setting the number of factors in the model, k , equal to N minimises $V(k)$, it does not imply N corresponds to the optimal number of factors r . [Bai and Ng \(2002\)](#) propose information criteria with a penalty function $g(N, T)$ such that:

$$r = \arg \min_{0 \leq k \leq k_{max}} \text{IC}(k) = \arg \min_{0 \leq k \leq k_{max}} \log(V(k)) + kg(N, T),$$

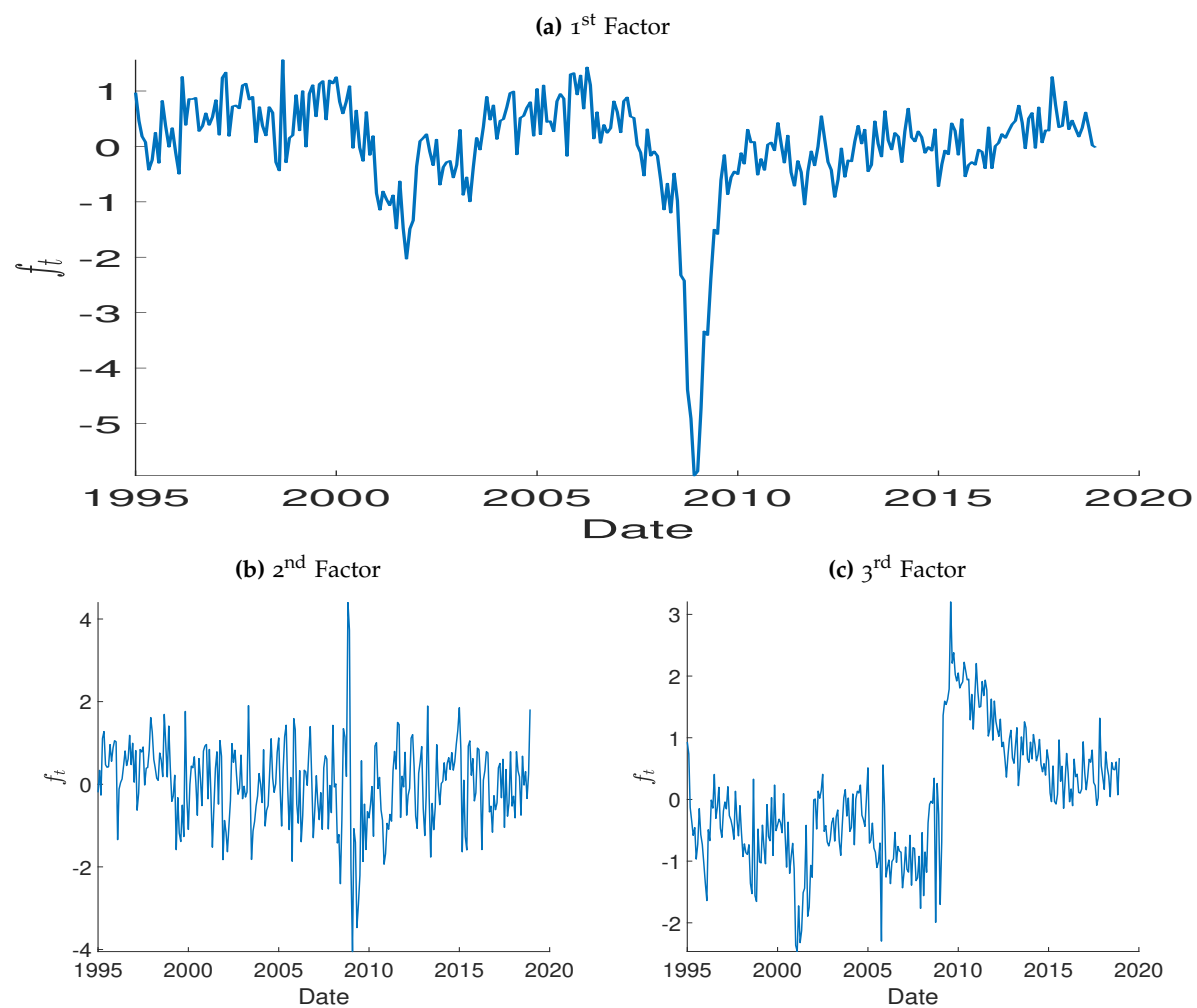
where $k_{max} \in \mathbb{N}$ is a maximum number of factors chosen by the researcher (here: $k_{max} = 9$). Due to the penalty term, $r \ll N$. [Choi and Jeong \(2019\)](#) compare the performance of different approaches and suggest to use several criteria in combination. We follow their recommendation and first evaluate [Bai and Ng's \(2002\)](#) IC_{p2} and BIC_3 which both pick $r = 9$ factors. Subsequently, we consider several criteria with improved robustness to miss-specification that are found to perform well in [Choi and Jeong \(2019\)](#). [Alessi et al. \(2010\)](#) propose modifications of the penalty functions in [Bai and Ng \(2002\)](#) based around an arbitrary constant, c , as in [Hallin and Liška \(2007\)](#). We set $c \in (0, 10]$ which leads to the conclusion that the optimal number of factors is either 1 or 3. [Kapetanios \(2010\)](#) suggests a criterion with improved robustness to cross-sectional dependence. When applying the [Alessi et al. \(2010\)](#) modification to this criterion, the optimal number of factors is again found to be 1 or 3. In accordance with the advice in [Choi and Jeong \(2019\)](#), we also considered the eigenvalue-based approaches in [Ahn and Horenstein \(2013\)](#). Both the ER and GR test imply 2, suggesting that a low number of factors is indeed a plausible choice. Therefore, 1 and 3 factors are deemed an appropriate choice for the empirical estimation in this paper.¹²

Interpretation – [Figure 1](#) depicts the squared correlation of the factors with each macro variable, categorised as described above. The first factor exhibits strong correlations with measures of output, labour market indicators as well as manufacturing orders and capacity utilisation. Therefore, we interpret the first factor as an indicator of real economic activity. The second factor correlates solely with long-term interest rates and inflation, wherefore it is deemed a monetary factor. In regards to the third factor, it displays strong correlations with the US housing sector and US interest rates. Logically, we interpret it as a housing factor which summarises the dynamics of the US housing market.

In [Figure 2](#), the individual time series of the factors are plotted. For the first factor, the drop in economic activity during the great recession is clearly visible and so is the burst of the dot-com bubble, albeit less pronounced. The principal component is also reflecting the somewhat slower recovery post-2009. Looking at the second factor, it implies a general co-movement between long-term interest rates and inflation with a stark temporary divergence in 2008. Finally, the housing factor exhibits a structural change after the subprime crisis and appears inversely related to the activity in the US housing sector.

¹²As the results remain sensitive to tuning parameters, [Appendix C](#) also reports the results for 5 factors.

Figure 2. Principal Components



5 Empirical Results

This section presents the empirical results of estimating the state space model (10) by comparing the constant and the time-varying parameter model. First, we discuss the fit of the models in-sample. Second, we devote a subsection to the issue of parameter instability to link the results back to the theoretical model; and third, we assess the out-of-sample performance of the two approaches.

5.1 In-Sample Comparison

The discussion of the in-sample results focuses on the GBP and the EUR while covering the remaining exchange rates more succinctly. To conduct a comparison of the two models, we use the squared correlation, R^2 , between the exchange rate and the in-sample predictions. Furthermore, we report the hit rate (HR) of each model, i.e. the percentage of times the model matched the signs of the exchange rate changes. The hit rate indicates how often a model correctly predicts a depreciation or appreciation. The two criteria are shown in Table 2.

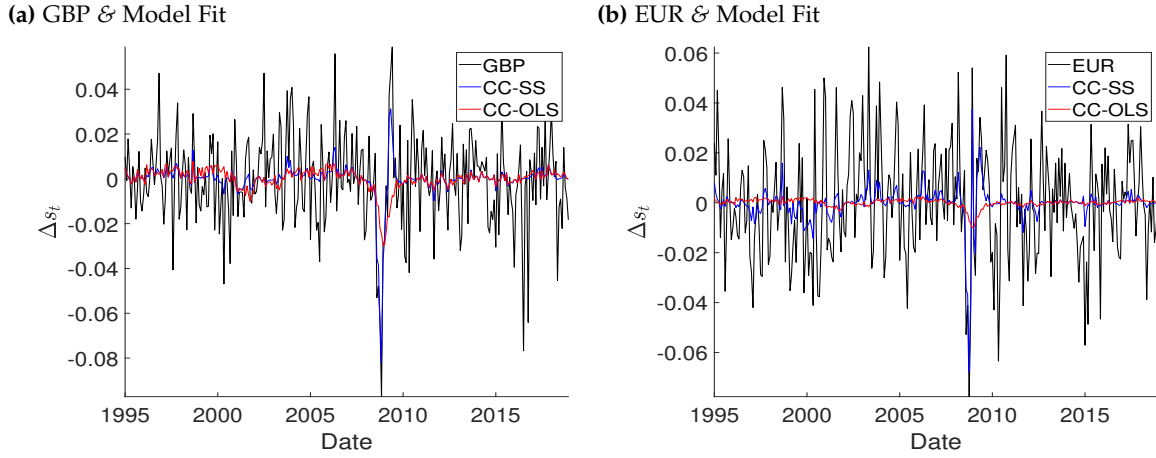
Table 2. In-Sample Performance

Currency	1 FACTOR				3 FACTORS			
	R^2		Hit Rate		R^2		Hit Rate	
	TVL	OLS	TVL	OLS	TVL	OLS	TVL	OLS
AUD	0.47	0.01	74.65	47.22	0.71	0.07	83.33	58.33
CAD	0.40	0.02	71.88	53.82	0.55	0.08	73.96	55.21
DKK	0.33	0.00	74.65	50.00	0.65	0.02	84.38	52.08
JPY	0.15	0.01	63.54	55.90	0.53	0.02	77.78	57.29
MXN	0.48	0.00	61.11	54.51	0.48	0.01	62.15	51.39
NZD	0.28	0.01	70.14	48.96	0.53	0.05	78.13	54.51
NOK	0.29	0.02	73.61	50.35	0.52	0.07	76.74	56.25
SEK	0.35	0.03	74.31	52.43	0.67	0.08	82.99	55.21
CHF	0.30	0.00	75.35	47.22	0.48	0.02	79.17	55.56
BRL	0.38	0.01	74.65	49.65	0.37	0.04	78.82	58.68
INR	0.51	0.01	70.14	51.04	0.88	0.02	86.81	49.31
ZAR	0.41	0.01	75.00	50.00	0.41	0.06	70.49	58.68
GBP	0.32	0.06	65.63	59.38	0.38	0.14	63.54	57.29
EUR	0.33	0.01	76.04	50.69	0.66	0.02	83.68	52.08

Note: The table reports measures of in-sample fit to compare the OLS and TVL model. Namely, both the squared correlations between changes in the exchange rate and the in-sample prediction of the TVP & OLS model as well as the hit rate in %. The latter being the times the sign of the fitted values corresponded to the sign of the realised values.

Consider first the estimates for one factor, the real economy factor. Figure 3 shows the results for the GBP and the EUR: the common component obtained from the time-varying model (blue), the OLS model (red), and the actual exchange rate changes (black). Particularly during the great recession, the time-varying model can capture the fluctuations in the exchange rate better. This is reflected in the R^2 , according to which the model can explain 33% (32%) of the variation in the EUR (GBP). It assigns accurate directional changes in 76% of the cases for the EUR and 66% for the GBP. In contrast, the OLS model only has an R^2 of 1% and 6%, respectively, i.e. it has almost no explanatory power. With 51%, the hit rate of the EUR model is as good as random, while it is slightly higher for

Figure 3. In-Sample Fit – Real Economy Indicator



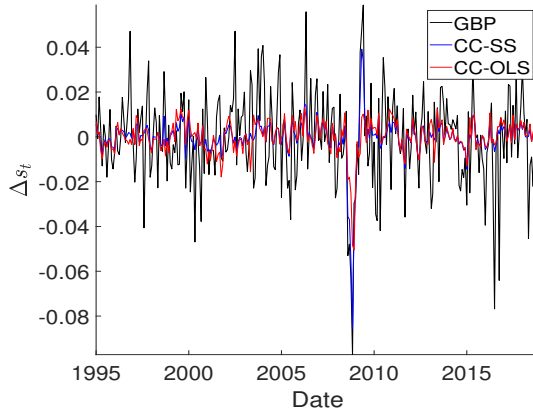
Note: The figure displays the results of a model estimated with only 1 factor, the real economy factor. The black line is the FX change, the blue line is the TVL model fit, and the red line is the OLS model fit.

the GBP with 59%. It should be noted that the OLS results for the GBP are the highest out of the 14 exchange rates. The lowest are the ones for CHF and DKK where 0% of the fluctuations are explained. Looking at the time-varying model it has the highest explanatory power for the INR with an R^2 of 50%, and the lowest for the JPY (15%). Nevertheless, this is considerably greater than the best OLS model (GBP with 6%). Therefore, the time-varying 1 factor model adds substantial explanatory power over the model with constant coefficients. Across currencies, it consistently outperforms the OLS model according to the two metrics.

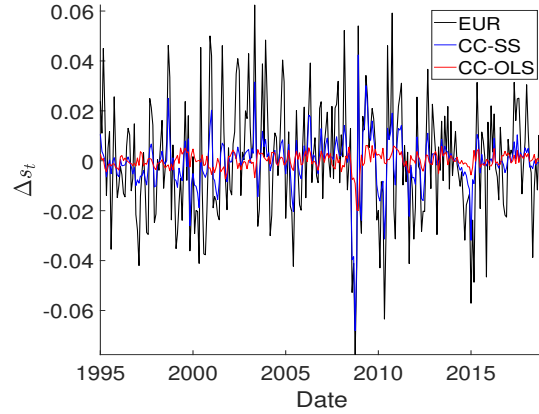
In a next step, we also include the monetary and the housing factor into the model. The actual and fitted values for the GBP and the EUR are presented in Figure 4. In particular for the EUR, the fit of the time-varying model improves visibly – the model tracks the depreciation during the Euro-crisis in 2010, 2012, and 2015 remarkably well. The same holds true for the early 2000s (see Figure 3 in comparison). The fit for the GBP also appears to have improved, even though to a lesser extent. Note that, as before, the GBP exhibits the second worst fit of all time-varying regressions with an R^2 of 38% followed by the BRL with 37%. Still, it manages to predict whether the exchange rate appreciates or depreciates in 64% of all cases. Regarding the EUR, the explanatory power of the time-varying model has doubled, amounting to an R^2 of 66%, and the hit rate corresponds to 84%. On the other hand, the OLS model only manages to explain 2% of the variations in the EUR and 14% in the GBP. The latter being the highest value for any of the 14 currencies. Overall, the time-varying model of the INR has the highest R^2 and hit rate with 88% and 87%, respectively. Followed by AUD, SEK, EUR, and DKK for which the explanatory power always exceeds 65%. Generally, we see an improvement in the R^2 across exchange rates – the hit rate declines slightly for the GBP and the ZAR in the time-varying framework but is close to 80% in most cases; however, looking at the OLS fit, it is still only marginally better than 50%.

Figure 4. In-Sample Fit – 3 Indicators

(a) GBP & Model Fit



(b) EUR & Model Fit



Note: The figure displays the results of a model estimated with 3 factors. The black line is the FX change, the blue line is the TVL model fit, and the red line is the OLS model fit.

For the remaining series, the 1 factor model is also able to capture exchange rate fluctuations better around the financial crisis (see [Figure C.1](#)). As was the case with the EUR and the GBP, the 3 factor model substantiates the ability of the time-varying model to outperform the constant parameter framework – notably so during currency or financial crises ([Figure C.2](#)). In the next subsection, we explicate the reasons behind this and shed additional light on the importance of accounting for structural instabilities in exchange rate regressions.

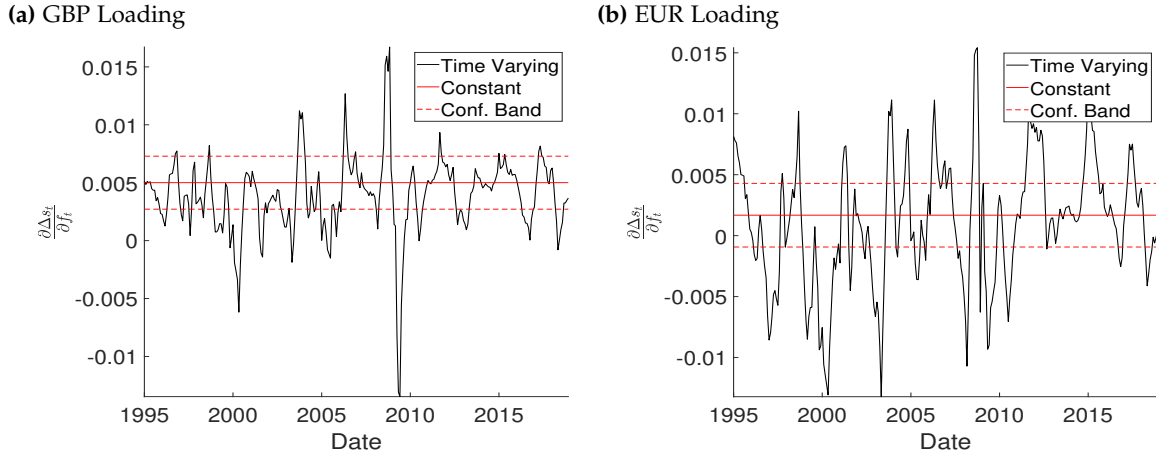
5.2 Parameter Instability

This subsection considers the role of parameter instability in greater detail. First, we revisit the GBP and the EUR and discuss the time-varying loadings on the real economy factor. Subsequently, we analyse instabilities in the 3 factor model by considering 3 major currency crises: (i) the Tequila-crisis of 1994, (ii) the Samba-crisis of 1999, and (iii) the Rand-crisis of 2001. Furthermore, we scrutinise the unstable effect of fundamentals on the CHF and the JPY, both of which are regarded as safe-havens for investors.

Structural Instabilities in GBP and EUR

[Figure 5](#) depicts the estimated factor loadings on the real economy indicator for the GBP and EUR. The dashed red lines correspond to the confidence intervals of the OLS estimates. For both currencies, we observe a high degree of variation in the time-varying loadings, especially in 2008-9. In the GBP model, the loading rose first and then declined sharply; therefore, being considerably outside the OLS confidence interval during the financial crisis. In the context of the theoretical model, an interpretation of this phenomenon is that investors deemed it likely that the British economy, given its large financial sector, was going to be disproportionately affected by the global financial crisis. Hence,

Figure 5. In-Sample Fit – Real Economy Indicator



Note: The figure displays the loadings on the real economy factor. The black line is the time-varying loading, the red line the OLS estimate, and the dashed lines are the OLS confidence intervals.

the decline in world output was associated with a fall in the GBP that exceeded its intertemporal equilibrium. Indeed, this is a consistent theme across exchange rates.¹³ The loading in the EUR model crosses the least-squares confidence bands more often, displaying large fluctuations throughout the sample period. However, the EUR least-squares estimate itself is insignificant. Contrary to the GBP, the loading exhibits large negative spikes in the early 2000s, consistent with the EUR depreciation vis-à-vis the dollar during that period.

Structural Instabilities During Currency Crises

Tequila-Crisis – In 1994/95, at the very start of the sample period, Mexico experienced a currency crisis that led to a financial and economic crisis. As part of a reform strategy the government introduced in the 1980, the central bank was commissioned to ensure a peg of the MXN to the USD. This was paired with increasing investor enthusiasm which, in hindsight, was unwarranted by fundamentals.¹⁴ In 1994, shifts in investor sentiment initiated a capital flight that continued throughout 1995.¹⁵ Eventually, this led to a drastic depreciation of the MXN as the central bank had to abandon the peg, an economic crisis, and a sharp increase in government debt which culminated in an international bail-out.¹⁶ Figure 6 (a) plots the loadings of the time varying model with three indicators for the MXN. It becomes clear that the second and third factor loadings play a relatively minor role compared to the real economy factor. The first loading captures the shift in investors' expectations about the

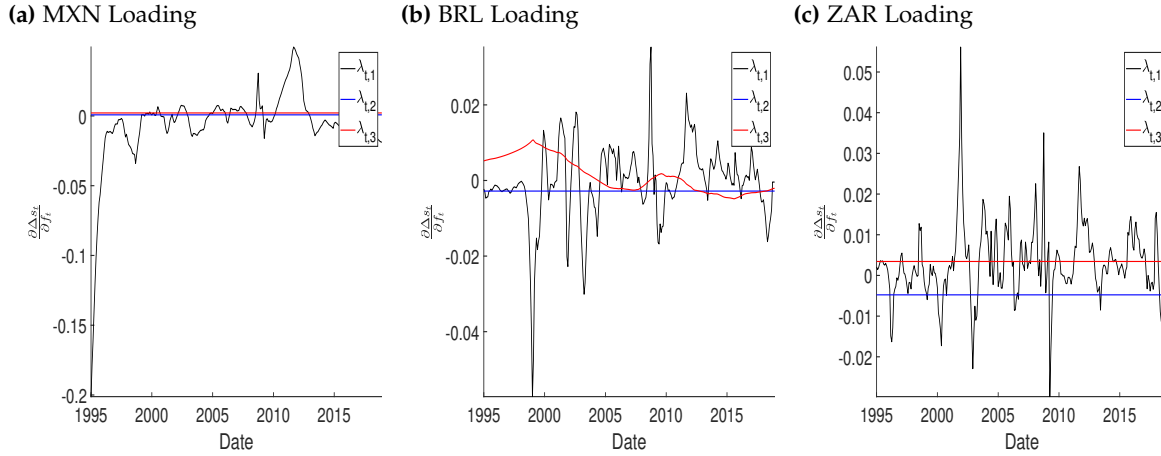
¹³The plots of the first factor loading for the remaining 12 currencies can be found in the [Appendix C](#).

¹⁴In 1993, a representative of Fidelity told the New York Times: "I am as convinced as I can be that the risk of an overnight major devaluation is extremely small" (Uchitelle, 1993).

¹⁵Most likely, this was sparked by several interest hikes in the US and the assassination of high-profile Mexican politicians, i.e. the president.

¹⁶Detailed discussions of the unfolding of the crisis can be found, for instance, in Whitt (1996) or Lustig (1995).

Figure 6. Structural Instabilities: Currency Crises



Note: The figure displays the loadings of the 3 factor model. The black line is the loading on the real economy factor, the blue line the loading on the monetary factor, and the red line the loading on the housing factor.

Mexican economy which originally initiated the capital flight from the MXN.

Samba-Crisis – [Figure 6 \(b\)](#) depicts the loadings for the BRL model. The drastic drop of the first loading in 1999 reflects Brazil’s currency crisis. In 1994, Brazil introduced a peg of the BRL to the USD as part of a programme to tackle its four digit inflation rates. A mixture of high government spending, a growing current account deficit, and the Asian financial crisis lead to capital outflows from Brazil, despite it being amongst the 10 largest economies in the world. Eventually, the central bank was forced to abandon its peg, leading to an economic crisis, an IMF bail-out, and a continuing depreciation until 2002.¹⁷ The loading on the real economy factor correctly captures the initial shock to investors’ expectations about Brazil’s economy that triggered these events.

Rand-Crisis – Contrary to the previous two examples, the 2001 Rand-Crisis was characterised by relatively stable macroeconomic conditions in South Africa, in comparison to Brazil and Mexico. Furthermore, the South African government abstained from interventions of the sort conducted in the other two countries. However, the depreciation coincided with a drop in world economic activity around the early 2000s, and weakening commodity prices.¹⁸ Hence, the loading on the first factor in [Figure 6 \(c\)](#) is positive, suggesting investors believed these negative developments could have repercussions for the South African economy that exceed the equilibrium impact of the cyclical movements in the global real economy.

These findings imply that, in all three cases, it were unobservable shocks associated with real economic conditions that occurred during – or translated into – a currency crisis. Plausible shocks in

¹⁷The NBER held a conference on the crisis in Brazil where these events and their implications were discussed in further detail [McHale \(2000\)](#).

¹⁸An overview of the currency crisis can, for example, be found in [Bhundia and Ricci \(2006\)](#).

line with the aforementioned circumstances are shifts in investors expectations about the business cycle in each country, an interpretation that is consistent with the Scapegoat theory of parameter expectations (Bacchetta and van Wincoop, 2013). The results do not suggest that monetary or housing market shocks triggered the respective crises. Appendix C contains the loadings on the first three factors for the remaining currencies. As Mikkelsen et al.'s (2019) methodology is robust to missing factors, the first loading is always identical to the one in the 1 factor model.

Structural Instabilities in Safe-Havens

For safe haven currencies, however, the shocks are of a different nature. To illustrate this, consider first the CHF: Figure 7 (a) shows the loadings of the 3 factor model. It can be seen that the most sizeable, and thus important, fluctuations occur in the loading on the monetary factor. The CHF appreciated strongly in the aftermath of the financial crisis in what can be perceived a flight to safety. In 2011, as a response to a rising demand for CHF, the Swiss National Bank introduced a peg vis-à-vis the EUR. This event is reflected in the the loading as well as a sudden depreciation of the CHF against the dollar, likely due to an anticipated decline in demand. In 2015, the Swiss National Bank famously abandoned its peg with the EUR, leading to a considerable appreciation against the latter. This event is again visible in the loading, although the CHF was never pegged against the dollar; therefore, one can interpret the shift in the loading as a monetary policy induced demand shock to the currency. The second safe haven currency considered is the JPY. Although the JPY also appreciated against the USD during the great recession for similar reasons as the CHF, it prior exhibited a strong continuing depreciation. The loadings estimates in Figure 7 (b) suggest this was also due to monetary policy shocks, reflected in the considerable fluctuations of the monetary factor loading.¹⁹ Indeed, the Bank of Japan pioneered zero interest rate policies and quantitative easing measure around the 2000s, and in subsequent years, which coincides with the spike of the associated loading. In both cases, CHF and JPY, these findings suggest that the episodic appreciation/depreciation was not due to unobservable shocks associated with the real economy, such as deteriorating investors' expectations, but primarily a result of monetary policy actions – contrary to the shocks during the currency crises discussed above.²⁰

5.3 Out-of-Sample Comparison

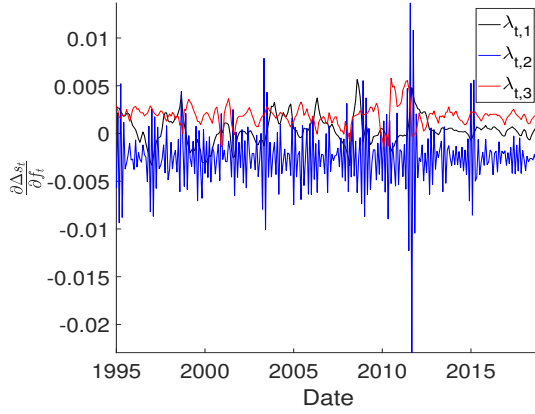
This section compares the performance of the two models out-of-sample, using the 3-factor model for this forecasting exercise. First, we elaborate on the chosen forecast evaluation methods; and second, assess the forecasting results. Specifically, we compare (i) the relative predictive ability of the two models, (ii) their direction accuracy, i.e. how well they forecast an appreciation or depreciation, and (ii) their relative performance over time.

¹⁹The plots for the remaining currency can be found in Appendix C

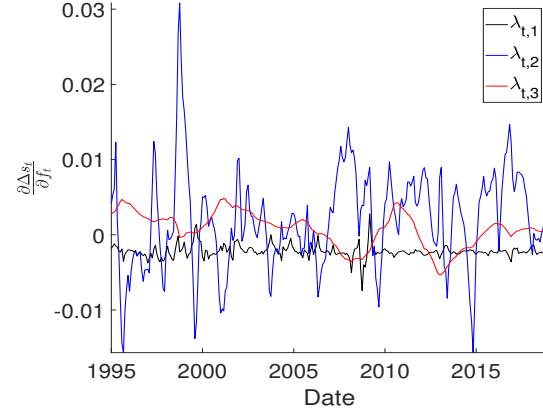
²⁰Although central banks responded to the currency crises in Mexico, Brazil, and South Africa, their policies did not prompt the initial capital flights, as outlined above.

Figure 7. Structural Instabilities: Safe-Haven Currencies

(a) CHF Loadings



(b) JPY Loadings



Note: The figure displays the loadings of the 3 factor model. The black line is the loading on the real economy factor, the blue line the loading on the monetary factor, and the red line the loading on the housing factor.

Forecast Construction and Evaluation

To forecast Δs_{t+h} , where h is the forecast horizon, we divide the sample into in-sample and out-of-sample portions. We denote the total number of observations by T , the number of in-sample observations by R , and the number of out-of-sample predictions by $P - h + 1$, so $T = R + P$. To remain consistent with the theoretical model, we generate direct h-step ahead forecast:²¹

$$\Delta s_{t+h|t} = f'_{t+h|t} \lambda_{t+h|t} + e_{t+h|t}$$

where $t = R, \dots, T - h$ and $e_{t+h|t}$ is the forecast error. We set $h = 1$, i.e. to one-step-ahead forecasts, and use a rolling window to compute P predictions. Forecasts for the loadings, $\hat{\lambda}_{t+h|t}$, are easily obtained as the one-step-ahead predictions of the Kalman filter. For the constant parameter benchmark, λ does not need to be forecasted as it simply corresponds to the OLS estimates at each iteration. Regarding the factors, consistent with the theoretical assumptions, we fit a VAR(1) to the in-sample estimates at each of the P steps and use the coefficients to forecast $\hat{f}_{t+h|t}$. One then obtains the out-of-sample estimates as $\widehat{\Delta s}_{t+h|t} = \hat{f}'_{t+h|t} \hat{\lambda}_{t+h|t}$ and $\widetilde{\Delta s}_{t+h|t} = \hat{f}'_{t+h|t} \hat{\lambda}_{OLS}$.

Relative Predictive Ability – Selecting adequate tests of predictive ability is of paramount importance in out-of-sample evaluation. As the evaluation in this paper is a comparison of nested models, the [Diebold and Mariano \(1995\)](#) test is unsuitable to assess which model produces better forecasts. In spite of its popularity in the exchange rate forecasting literature, the [Diebold and Mariano \(1995\)](#) test was never intended for model comparison ([Diebold, 2015](#)). The properties of tests for nested models are different because their forecast errors converge asymptotically ([Clark and McCracken,](#)

²¹See [Boivin and Ng \(2005\)](#) for a comparison of different approaches to generating factor-based forecasts. An alternative – inconsistent with the theoretical model – is to use $\Delta s_{t+h} = f'_t \lambda_t + e_{t+h|t}$ to generate forecasts. This approach is found in [Engel et al. \(2014\)](#), among others.

2001). Furthermore, window choice is an important determinant in forecast evaluation. A large P provides more forecast information, while a large R improves parameter accuracy. In fact, [Mikkelsen et al. \(2019\)](#) show through Monte-Carlo simulations that in order for the bias in the autoregressive parameters of the loadings to be below 10%, the estimation sample should be $R \geq 200$. However, a litmus test for every exchange rate forecast is the financial crisis. To put the model to this test, the forecasts need to be evaluated using a criterion that is robust to in-sample estimation errors, as one would have $R < 200$ for a prediction window starting prior to the crisis. While the [Diebold and Mariano \(1995\)](#) test depends on the probability limits of the parameters, [Giacomini and White \(2006\)](#) propose a test of conditional predictive ability that introduces estimation error under the null hypothesis:

$$\mathcal{H}_0 : \mathbb{E} \left[\mathcal{L}_{t+h}(\Delta s_{t+h}, \hat{f}'_{t+h|t} \hat{\lambda}_{t+h|t}) - \mathcal{L}_{t+h}(\Delta s_{t+h}, \hat{f}'_{t+h|t} \hat{\lambda}_{OLS}) | \mathcal{F}_t \right] = 0$$

Where $\mathcal{L}(\cdot)$ is a forecast loss function and $\mathcal{F}_t$ is the time- t information set. As the asymptotic properties of this test are derived for $R < P \rightarrow \infty$, it is well-suited in this application. we choose $P = 150$ and $R = 133$ as the baseline horizon and report additional forecasts in the appendix.

Direction Accuracy – [Leitch and Tanner \(1991\)](#) argue that, while one model may produce a smaller forecasting error than another model, it can still perform worse when it comes to predicting sign changes. In case of exchange rates, a desirable feature of a model is its ability to forecast an appreciation or depreciation. To assess this statistically, we use [Pesaran and Timmermann's \(1992\)](#) nonparametric test of predictive performance. The test compares the signs of the predicted and realised values and, in doing so, uses no additional information. Thus, it does not require knowledge of the underlying probability distribution of the forecast. Although the test does not put two models in relation to one another, it indicates which model is able to identify a higher number of predictable relationships.

Forecast Evaluation under Instabilities – Given the structural instabilities in the exchange rate regression, it may well be the case that the relative forecasting performance of the models is itself unstable. Indeed, [Rossi \(2013\)](#) finds that the forecasting power of many exchange rate models breaks down over time. Notably, however, parameter instability itself does not necessarily engender unstable relative forecast performance.²² While the [Giacomini and White \(2006\)](#) test selects the best global model, [Giacomini and Rossi \(2010\)](#) propose a fluctuation test that compares the performance of the two competing models at each point in time and allows for nested models by adopting the same asymptotic framework as [Giacomini and White \(2006\)](#). Let $\{\Delta \mathcal{L}_t(\hat{f}'_t \hat{\lambda}_t, \hat{f}'_t \hat{\lambda}_{OLS})\}_{t=R+h}^T = \{\mathcal{L}(\Delta s_t, \hat{f}'_t \hat{\lambda}_t) - \mathcal{L}(\Delta s_t, \hat{f}'_t \hat{\lambda}_{OLS})\}_{t=R+h}^T$ be the loss differential. The test statistic is computed over a rolling window and equal to:

$$GR_{t,m} = \hat{\sigma}^{-1} m^{-1/2} \sum_{j=t-m/2}^{t+m/2-1} \Delta \mathcal{L}_j(\hat{f}'_{j,R} \hat{\lambda}_{j,R}, \hat{f}'_{j,R} \hat{\lambda}_{OLS})$$

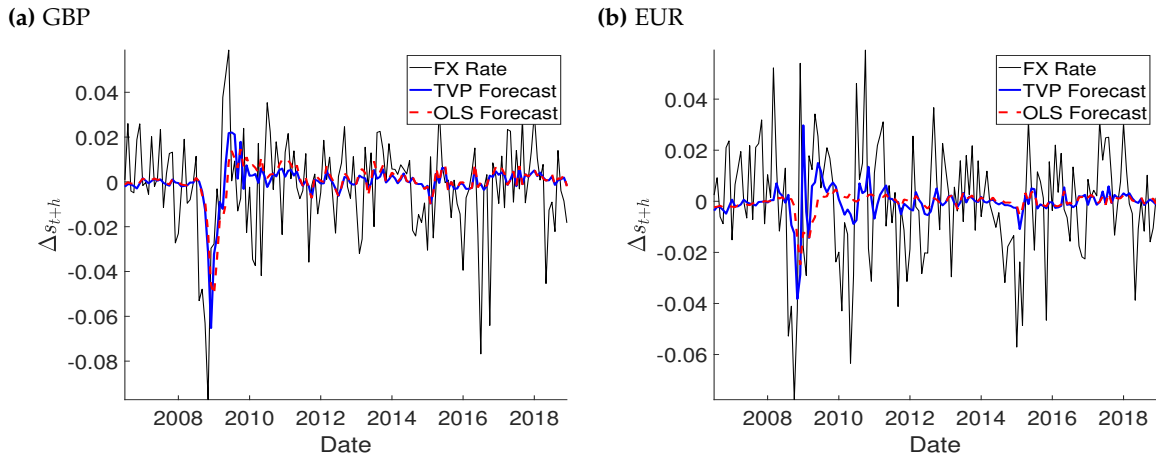
²²For a detailed discussion of forecasting under instabilities, see [Rossi \(2020\)](#).

where $t = R + h + m/2, \dots, T - m/2 + 1$, $\hat{\sigma}$ is the HAC estimator of the variance of the loss differential, and m is the size of the rolling window over which it is computed.

Forecast Results

Focusing foremost on GBP and EUR, we now discuss the forecasting results. Figure 8 depicts the time-varying and OLS forecasts for the two currencies as well as the realised values. At first glance, it appears the time-varying model performs slightly better for the GBP during the financial crisis – and for the EUR also during the subsequent years. Figure 9 plots the forecasts of the remaining series which paint a similar picture; in particular the INR (Figure 9 (f)) is forecasted remarkably well.

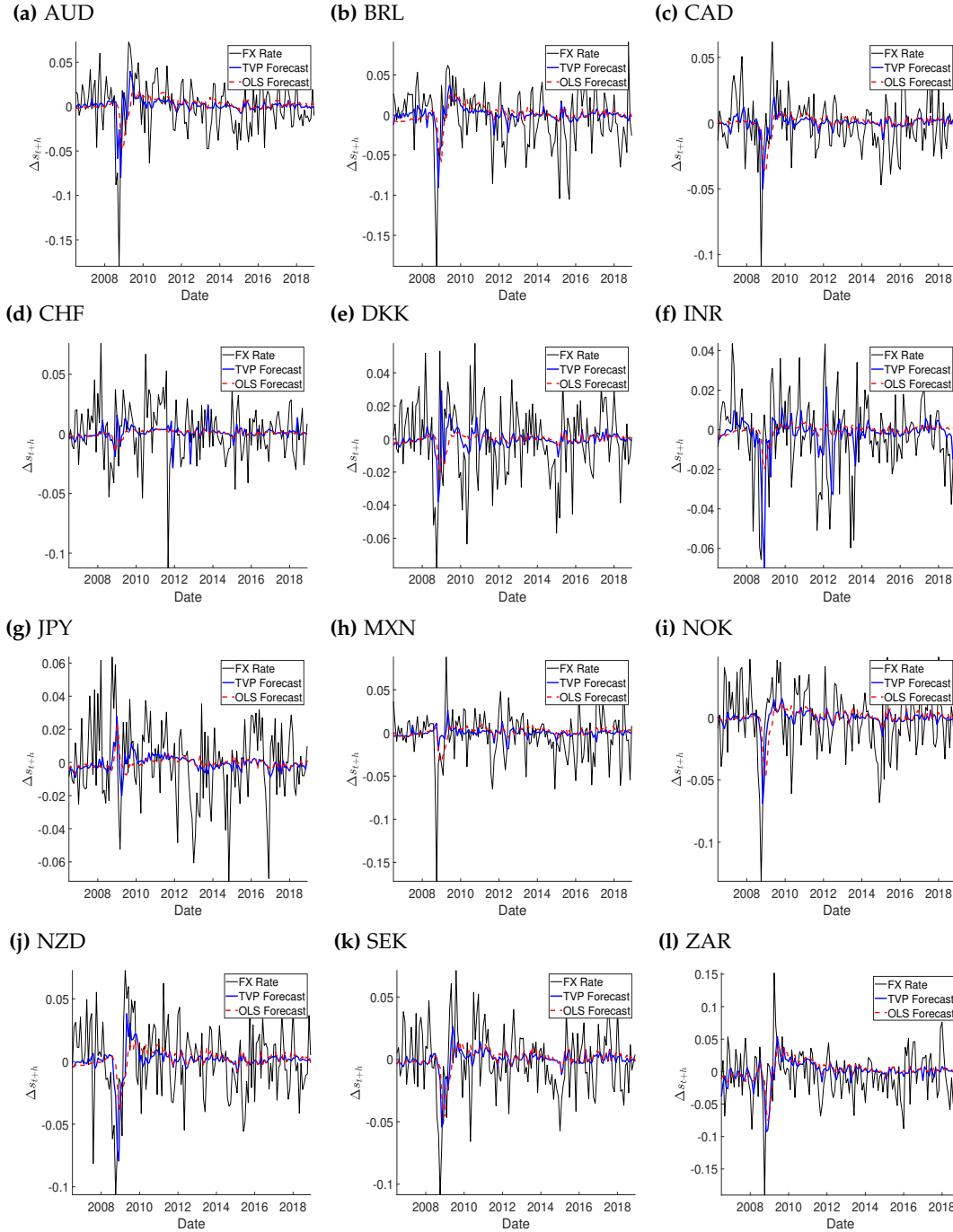
Figure 8. Rolling Window Forecast I



Note: This figure plots the out-of-sample, one-step-ahead, rolling window forecasting results of the time-varying (blue line) and the constant loadings (red line) model. The black line corresponds to the actual exchange rate.

The first two columns of Table 3 report the Root Mean Square Error (RMSE) of the forecasts, and the third column indicates whether the difference between them is negative (i.e. the OLS model exhibits a larger RMSE) or positive (i.e. the OLS model has a smaller RMSE). This latter case only materialises itself for three of the 14 currencies. Columns 5 and 6 show the results of the Giacomini and White (2006) test using a quadratic loss function. The test rejects the null hypothesis of equal predictive ability at the 5% level for BRL, NOK, and AUD and at the 10% level for the DKK – always in favour of the time-varying model. Farther, we perform the Giacomini and White (2006) test using the absolute forecast loss. As columns 7 and 8 report, the test rejects the null hypothesis for EUR, BRL, NOK, DKK, AUD (all at the 10% level) and for the SEK at the 5% level. As the loss function differential is negative in all 6 cases, the results demonstrate the improved global predictive ability of the time-varying relative to the constant model. The last four columns evaluate the two models individually through the Pesaran and Timmermann (1992) direction accuracy test. Regarding the time-varying model, we reject the null hypothesis of no predictable relationships 7 times: at the 1% level for the JPY, at the 5% level for ZAR and GBP, and at the 10% level for AUD, CAD, MXN, and INR. In contrast, for the constant loadings model, the null hypothesis is only rejected 4 times: for the

Figure 9. Rolling Window Forecast II



Note: This figure plots the out-of-sample, one-step-ahead, rolling window forecasting results of the time-varying (blue line) and the constant loadings (red line) model. The black line corresponds to the actual exchange rate.

Table 3. Forecast Statistics

Currency	RMSE			Giacomini-White				Pesaran-Timmermann			
				$\mathcal{L}$: Quadratic		$\mathcal{L}$: Absolute		TVL		OLS	
	TVL	OLS	Δ	p-val	Stat.	p-val	Stat.	p-val	Stat.	p-val.	Stat.
AUD	0.028	0.031	-	0.041**	6.389	0.098*	4.640	0.051*	1.635	0.523	-0.057
CAD	0.020	0.021	-	0.270	2.618	0.626	0.937	0.085*	1.372	0.069*	1.484
DKK	0.022	0.023	-	0.097*	4.657	0.099*	4.630	0.468	0.080	0.505*	-0.013
JPY	0.023	0.024	-	0.358	2.056	0.645	0.876	0.010***	2.337	0.033**	1.835
MXN	0.030	0.029	+	0.500	1.384	0.679	0.774	0.071*	1.467	0.213	0.794
NZD	0.028	0.029	-	0.319	2.287	0.103	4.543	0.684	-0.478	0.955	-1.694
NOK	0.026	0.027	-	0.050**	6.010	0.046*	6.148	0.125	1.149	0.461	0.097
SEK	0.025	0.026	-	0.101	4.588	0.014**	8.560	0.677	-0.459	0.711	-0.555
CHF	0.024	0.024	+	0.644	0.879	0.382	1.927	0.855	-1.057	0.793	-0.818
BRL	0.036	0.038	-	0.018**	8.045	0.082*	5.006	0.206	0.822	0.745	-0.660
INR	0.021	0.020	+	0.866	0.287	0.981	0.038	0.079*	1.413	0.952	-1.666
ZAR	0.039	0.039	-	0.626	0.938	0.770	0.522	0.021**	2.039	0.229	0.741
GBP	0.021	0.022	-	0.166	3.586	0.729	0.631	0.011**	2.306	0.006***	2.542
EUR	0.023	0.023	-	0.117	4.297	0.097*	4.658	0.600	-0.252	0.634	-0.341

Note: The table reports the Root Mean square Error (RMSE) of the forecasts and the sign of the difference between them. A (-) indicates that the OLS model has a greater RMSE. It also reports results of the [Giacomini and White \(2006\)](#) test for conditional predictive ability using a quadratic and an absolute loss function. The sign of the average of the quadratic loss function differential necessarily corresponds to the one of the RMSE difference. This is not necessarily true for the absolute loss function where the difference is negative for the CHF and positive for the ZAR. The test is insignificant for both, hence the table only reports the sign of the RMSE differential. Further it reports the reports of the [Pesaran and Timmermann \(1992\)](#) nonparametric direction accuracy test.

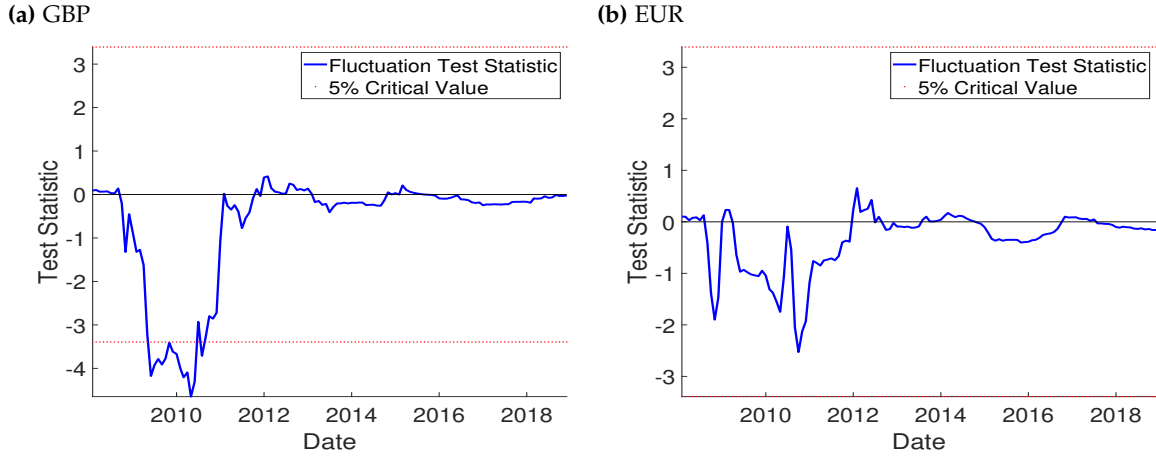
***: $p \leq 0.01$, **: $p \leq 0.05$, *: $p \leq 0.1$

GBP (1% level), for the JPY (5% level), and for CAD and DKK (10% level). All in all, the time-varying model has better global out-of-sample predictive ability, and withal better forecasts exchange rate changes.

In addition to selecting a model based on relative global predictive ability, it is interesting to examine how the relative predictive ability of two models changes over time. [Figure 10](#) plots the results of the [Giacomini and White \(2006\)](#) fluctuation test for GBP and EUR. The blue line represents the test statistic at each point in time and the red lines represent the 5% critical values. The results are obtained using a rolling window of $m = 20$ and a quadratic loss function. When the test statistic lies below the critical value, the null hypothesis of equal predictive ability is rejected in favour of the time-varying model. This is the case for the GBP during the financial crisis. Although the [Giacomini and White \(2006\)](#) test did not provide evidence that the time-varying model is globally more accurate in case of the GBP (see [Table 3](#)), the [Giacomini and Rossi \(2010\)](#) fluctuation test rejects the null hypothesis of equal predictive ability during the financial crisis. [Figure 11](#) shows the results for the remaining currencies. Apart from the GBP, the fluctuation test also rejects the null hypothesis for AUD, BRL, JPY, NOK, NZD, and SEK.²³ The [Giacomini and White \(2006\)](#) test only rejected the null hypothesis of equal predictive ability at the 5% level for AUD, NOK, and BRL ([Table 3](#)). That is, for an additional 4 currencies, we find evidence that accounting for structural instabilities leads to improved local predictive ability during the financial crisis. The test statistic never attains the positive critical value, meaning the null hypothesis is never rejected in favour of the constant parameter model.

²³The NZD test statistic exceeds the critical value by a very small margin.

Figure 10. Giacomini-Rossi Fluctuation Test I



Note: This figure plots the results of the [Giacomini and Rossi \(2010\)](#) fluctuation test. The solid blue line is the test statistic, the dotted red lines are the 5% critical values. The results are based on a rolling window of $m = 20$ and a quadratic loss function.

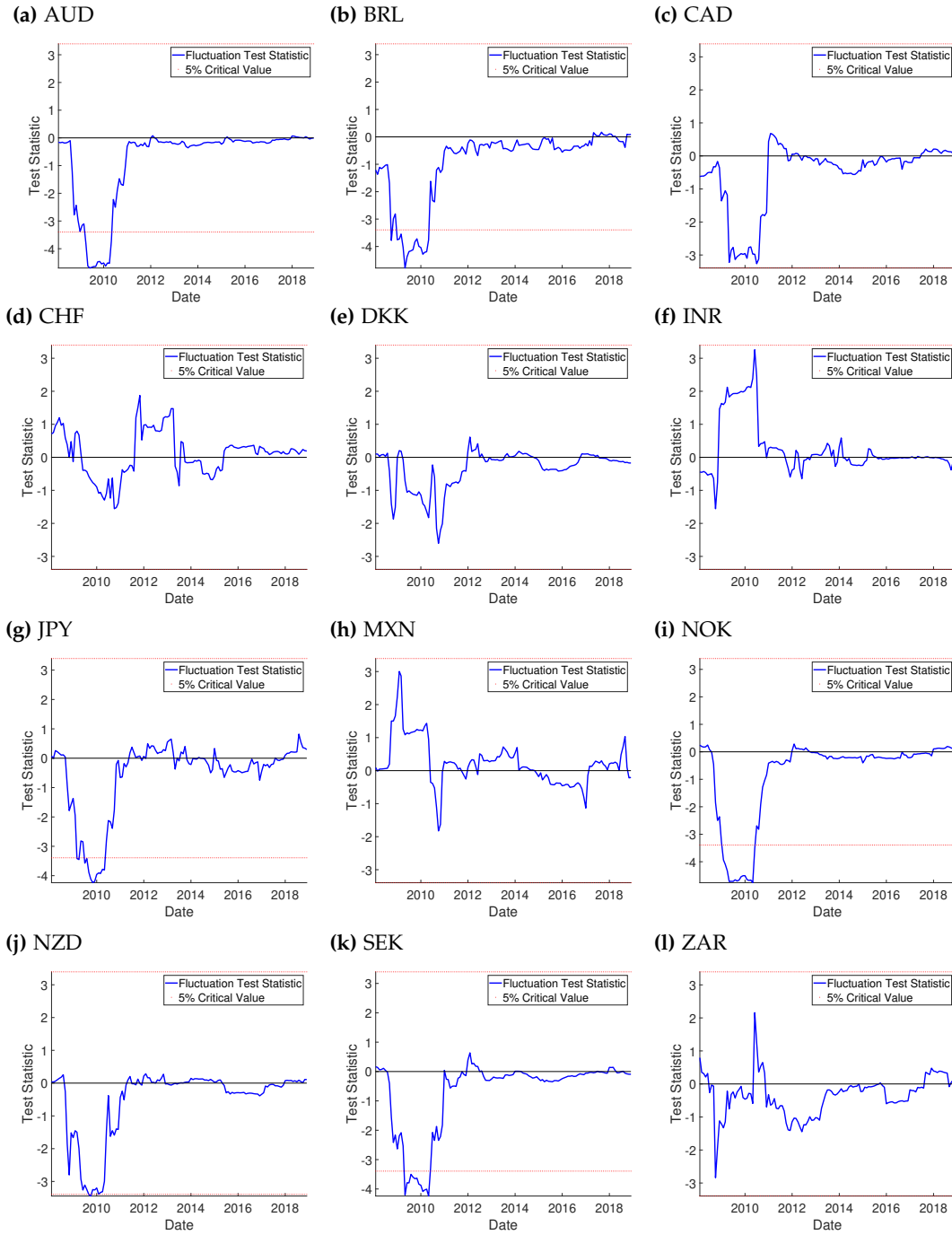
5.4 Robustness and Critical Assessment

As discussed above, several factor selection criteria suggested a low number of factors, no higher than 3, is an appropriate choice given the dataset. Nevertheless, to further underpin the robustness of the in-sample findings, we re-estimate the model using 5 factors. The results are reported in [Appendix D.1](#). While the R^2 for the OLS model improves, it remains considerably lower than the one of the time-varying model across all currencies. The same holds true for the hit-rate which ranges between 70% and 90% for the time-varying and 50% to 65% for the OLS model. Regarding the out-of-sample findings, we use the 1 factor model to generate forecasts over the same horizon as above and report the statistical evaluation in [Appendix D.2](#). The results are equally – if not more – affirmative. Neither the [Giacomini and White \(2006\)](#) nor the [Pesaran and Timmermann \(1992\)](#) test find any predictive ability on the part of the constant parameter model (see [Table D-2](#)). In addition, [Appendix D.2](#) contains the forecast evaluation for the 3 factor model over different prediction horizons ($P = 100$ and $P = 180$). In all cases, the evidence stands clearly in favour of the time-varying model. The computational complexity of the algorithm does not allow for the use of forecast evaluation criteria as in [Rossi and Inoue \(2012\)](#) that are robust to estimation window size. However, the robustness checks in conjunction with the three different forecast evaluation criteria should eliminate concerns that the out-of-sample results are driven by window size.

6 Conclusions

In this paper, we studied the unstable relationship between exchange rates and macroeconomic fundamentals. Using a model that relates foreign exchange rates with macroeconomic factors, we showed that allowing for time-varying loadings increases the percentage of explained variation in

Figure 11. Giacomini-Rossi Fluctuation Test II



Note: This figure plots the results of the [Giacomini and Rossi \(2010\)](#) fluctuation test. The solid blue line is the test statistic, the dotted red lines are the 5% critical values. The results are based on a rolling window of $m = 20$ and a quadratic loss function.

exchanges rates by an order of magnitude. In addition, taking the aforementioned instabilities into consideration improves the relative out-of-sample predictive ability of the model globally, and yields better forecast of sign changes in exchange rates.

We extracted macroeconomic fundamentals from a dataset of 290 variables spanning from 1994:12 to 2018:12 and estimate the unobservable shocks using a time-varying factor model (Mikkelsen et al., 2019). The model is applied to 14 currencies vis-à-vis the US Dollar and the results show that failure to account for the instabilities between exchange rates and fundamentals is by no means innocuous. In-sample, the R^2 improves between 24 and up to 86 percentage points, depending on the currency. By discussing how the time-varying loadings estimates align with economic developments, we set the empirical findings into theoretical context. We showed that out-of-sample, the time-varying model exhibits either significantly better forecast accuracy, or performs at least as good as the constant parameter model. When evaluating the forecasts individually, the time-varying model outperformed the benchmark at predicting directional exchange rate changes, i.e. an appreciation or depreciation. To consider potentially unstable forecasting performance, we evaluated the relative predictive accuracy of the forecasts using the Giacomini and Rossi (2010) fluctuation test. In addition to higher global forecast accuracy, including unobserved transitory shocks that impact the equilibrium relation between exchange rates and fundamentals, improved forecasts locally around the financial crisis. This paper provides strong evidence that the relationship between macroeconomic fundamentals and exchange rates is highly unstable.

At the time of writing, the SARS-Cov-2 pandemic is ongoing and for many macroeconomic variables data availability is still limited and measurement errors may be pervasive – particularly in non-OECD countries. Highly preliminary estimations, using the data available thus far, suggest the conclusions drawn in this paper remain unaltered. However, especially the local out-of-sample performance during the pandemic is difficult to examine as the data only reflects the start of the crisis. It remains to be seen whether the transformations applied in McCracken and Ng (2016) and this paper remain adequate to ensure stationarity in light of the extreme fluctuations observed in 2020. Revisiting the role of structural instabilities once the pandemic has abated and reliable data is widely available may provide additional insights. Some conventional econometric models, such as VARs, may be unable to handle the extreme observations recorded in 2020 (Lenza and Primiceri, 2020). However, the methodology applied in this paper could prove to be a useful forecasting tool, as it can be extended to allow for different, non-stationary dynamics of the factors. In light of the improved predictive ability of the time-varying model, future research could explore its performance in comparison to different exchange rate models, especially time-varying VAR models.

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We are grateful to Lucio Sarno and Ian Marsh for helpful comments. We thank seminar participants at CREATES, the University of Maastricht, the Tinbergen Institute, and Oxford University for very helpful comments and suggestions on a previous version of the paper. However, the usual disclaimer applies. J.G. Mikkelsen and E. Hillebrand acknowledge support from The Danish Independent Research Fund. We also acknowledge financial support from the Centre for Econometric Analysis.

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Appendices

A Derivation of Real Interest Rates and Fundamentals

Recall (3):

$$r_t^* - r_t = -f_t'(\beta + \kappa_t)$$

To see how this equation relates to known models of fundamentals, consider a monetary policy rule of the form in [Clarida et al. \(2000\)](#):

$$\tilde{i}_t = \tilde{\psi}_{0,t} + \psi_1(\pi_t - \tilde{\pi}) + \psi_2(y_t - \tilde{y}_t)$$

where $\tilde{i}_t$ is the target interest rate, $\tilde{\psi}_{0,t}$ is the neutral interest rate, and $y_t - \tilde{y}_t$ is the output gap, i.e. the deviation of output growth from its potential. Inflation as well as output and its potential are denoted as log differences, i.e. $\ln(P_t/P_{t-1})$, $\ln(Y_t/Y_{t-1})$, and $\ln(\tilde{Y}_t/\tilde{Y}_{t-1})$. The central bank aims to balance interest rates such that the output gap is closed and inflation is aligned with the inflation target. The central bank conducts interest rate smoothing to close the gap between its rule-implied interest rate and the past level:

$$i_t = (1 - \theta)\tilde{i}_t + \theta i_{t-1}$$

Which we can rearrange to

$$r_t = (1 - \theta)\tilde{i}_t + \theta i_{t-1} - \mathbb{E}[\pi_{t+1}]$$

Equal rules are assumed for the foreign country.²⁴ After substituting the target interest rate rule into the equation for the real interest rate, we obtain:

$$r_t = (1 - \theta)\{\tilde{\psi}_{0,t} - \psi_1\tilde{\pi} + \psi_1\pi_t + \psi_2(y_t - \tilde{y}_t)\} - \mathbb{E}_t[\pi_{t+1}] + \theta i_{t-1}$$

Rearranging yields:

$$\begin{aligned} r_t &\approx (\beta_0 + (1 - \theta)\tilde{\psi}_{0,t}) + \pi_t \left[\beta_1 - \frac{\ln(1 + \mathbb{E}_t[\pi_{t+1}])}{\ln(1 + \pi_t)} \right] + y_t \left[\beta_2 - \beta_2 \frac{\ln(1 + \tilde{y}_t)}{\ln(1 + y_t)} \right] + \theta i_{t-1} \\ &= (\beta_0 + \kappa_{0,t}) + \pi_t [\beta_1 - \kappa_{1,t}] + y_t [\beta_2 - \kappa_{2,t}] + \theta i_{t-1} \\ &= f_t'(\beta + \kappa_t) \end{aligned}$$

where the long-run equilibrium relationships are defined by: $\beta_0 = (1 - \theta)\psi_1\tilde{\pi}$, $\beta_1 = (1 - \theta)\psi_1$, and $\beta_2 = (1 - \theta)\psi_2$ as well as θ . So $\beta = (\beta_0, \beta_1, \beta_2, \theta)$. The fundamentals are: $f_t = (1, \pi_t, y_t, i_{t-1})$, where the first term is an intercept. The unobserved shocks are $\kappa_{0,t} = (1 - \theta)\tilde{\psi}_{0,t}$, $\kappa_{1,t} = \frac{\ln(1 + \mathbb{E}_t[\pi_{t+1}])}{\ln(1 + \pi_t)}$, and $\kappa_{2,t} = \beta_2 \frac{\ln(1 + \tilde{y}_t)}{\ln(1 + y_t)}$. Consequently, $\kappa_t = (\kappa_{0,t}, \kappa_{1,t}, \kappa_{2,t}, 0)$; clearly, there are no unobserved shocks to past interest rates. After subtracting the equivalent foreign rule, we obtain (3), where the respective foreign variables populate the three vectors (β, f_t, κ_t) with opposite signs. Changes in inflation expectations or the potential level of output – both unobservable – *relative* to actual inflation and output constitute an unobserved shock that alters the short-run relationship of output or inflation with real interest rates.

²⁴Assuming a different set-up still yields (3).

B Data Summary

Table B-1. Data Summary

Series	Cat.	Unit	AUD	CAD	DKK	JPY	MXN	NZD	NOK	SEK	CHF	GBP	EUR	BRL	INR	ZAR
Industrial production	1	Idx.	✗	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗
Total manufacturing	1	Idx.	✗	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓
Construction	1	Idx.	✗	✓	✗	✓	✓	✗	✗	✓	✗	✓	✓	✓	✗	✓
Retail trade (Volume)	4	Idx.	✗	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✗	✓
Passenger car registrations	4	Idx.	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✗	✓	✓
Permits issued for dwellings	3	Idx.	✓	✓	✗	✗	✗	✓	✓	✓	✗	✗	✓	✗	✗	✓
Manufacturing - Confidence indicator	1	%	✗	✗	✓	✗	✓ [†]	✗	✗	✓	✗	✓	✓	✓	✗	✗
Consumer confidence indicator	4	%	✓	✗	✓	✓	✓	✗	✗	✓	✗	✓	✓	✓ [†]	✗	✗
Employment; all persons	2	Lvl.	✓	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
Unemployment rate: all persons	2	%	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✗	✗	✗
Hourly earnings: manufacturing	2	Idx.	✗	✓	✗	✓	✓	✗	✗	✓	✗	✓	✗	✗	✗	✗
Producer prices - Manufacturing	7	Idx.	✗	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✗	✗	✗
Consumer prices: all items	7	Idx.	✗	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓
Narrow money	5	Idx.	✓	✓	✓	✓	✓ [‡]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Broad money	5	Idx.	✓	✓	✓	✓	✓ [‡]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Goods Exports	1	\$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Goods Imports	1	\$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3-month yield	6	%	✗	✗	✗	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓
6-month yield	6	%	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2-year yield	6	%	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✓
10-year yield	6	%	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓ [*]	✗	✓	✓

Note: A ✓ indicates consistent availability for the respective country, a ✗ indicates no consistent availability. Consistent means there are no missing values between 1994:12 and 2018:12. Cat. refers to [McCracken and Ng \(2016\)](#) categories into which each series is sorted: (1) Output & Income, (2) Labour Market, (3) Housing, (4) Orders & Inventories, (5) Money & Credit, (6) Interest Rates, (7) Prices, and (8) Stock Markets. Unit refers to original unit in OECD database. Idx. stands for Index (2015=100), % denotes annualised percentages, Lvl. number of 1000 persons, and \$ stands for US-\$ billions. All variables not in % are transformed using first log differences ($\Delta \log$), variables in % are transformed using first differences Δ , consistent with [McCracken and Ng \(2016\)](#).

[†] Unit of variable is Index. Transformation is $\Delta \log$.

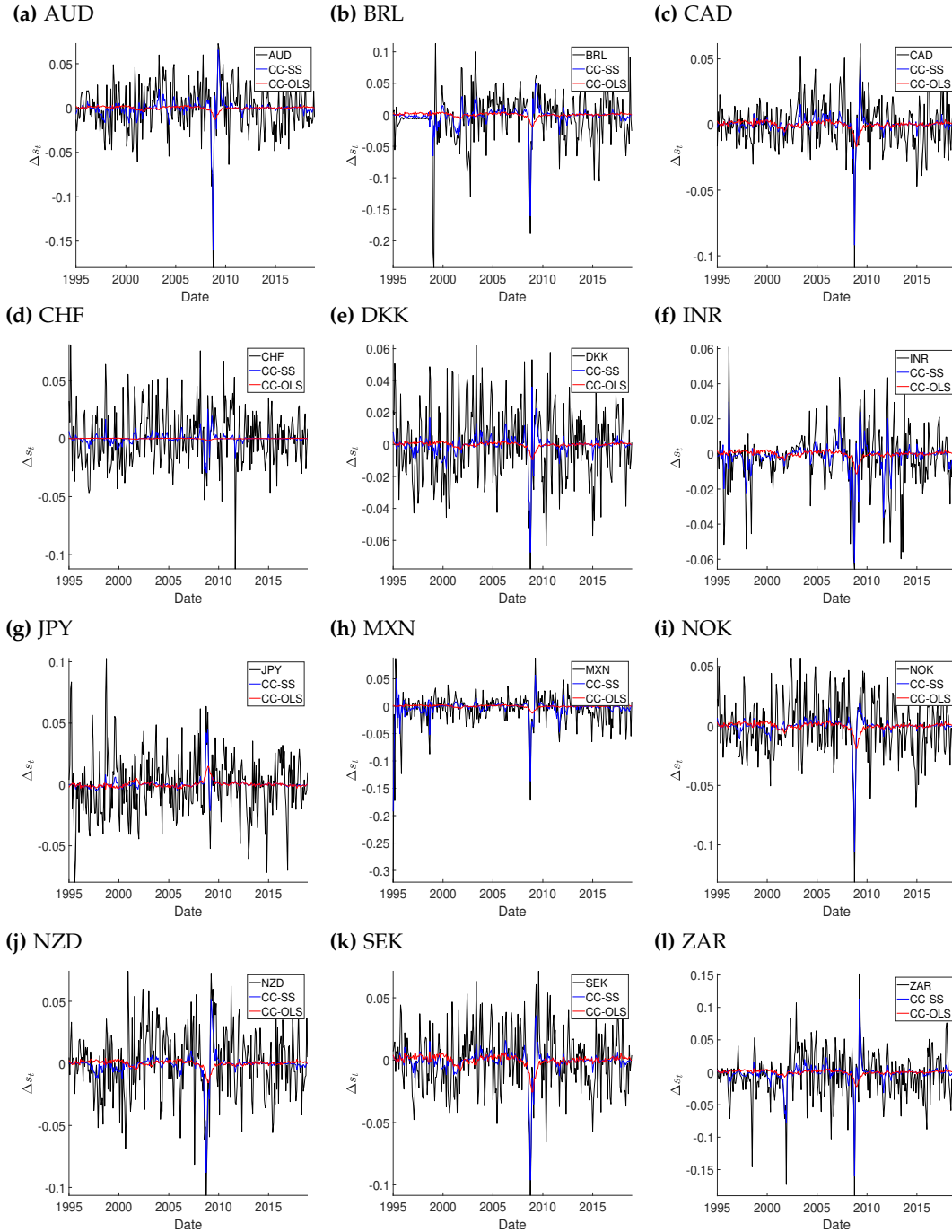
[‡] Unit of variable is Mexican Peso. Transformation is Δ .

* Euro area benchmark yield is typically German 10-year bond. To capture the fiscal situation of other Euro member states, we also include Finland, France, Ireland, Italy, the Netherlands, and Spain.

Source: All OECD, as of May 2020. Raw data available upon request.

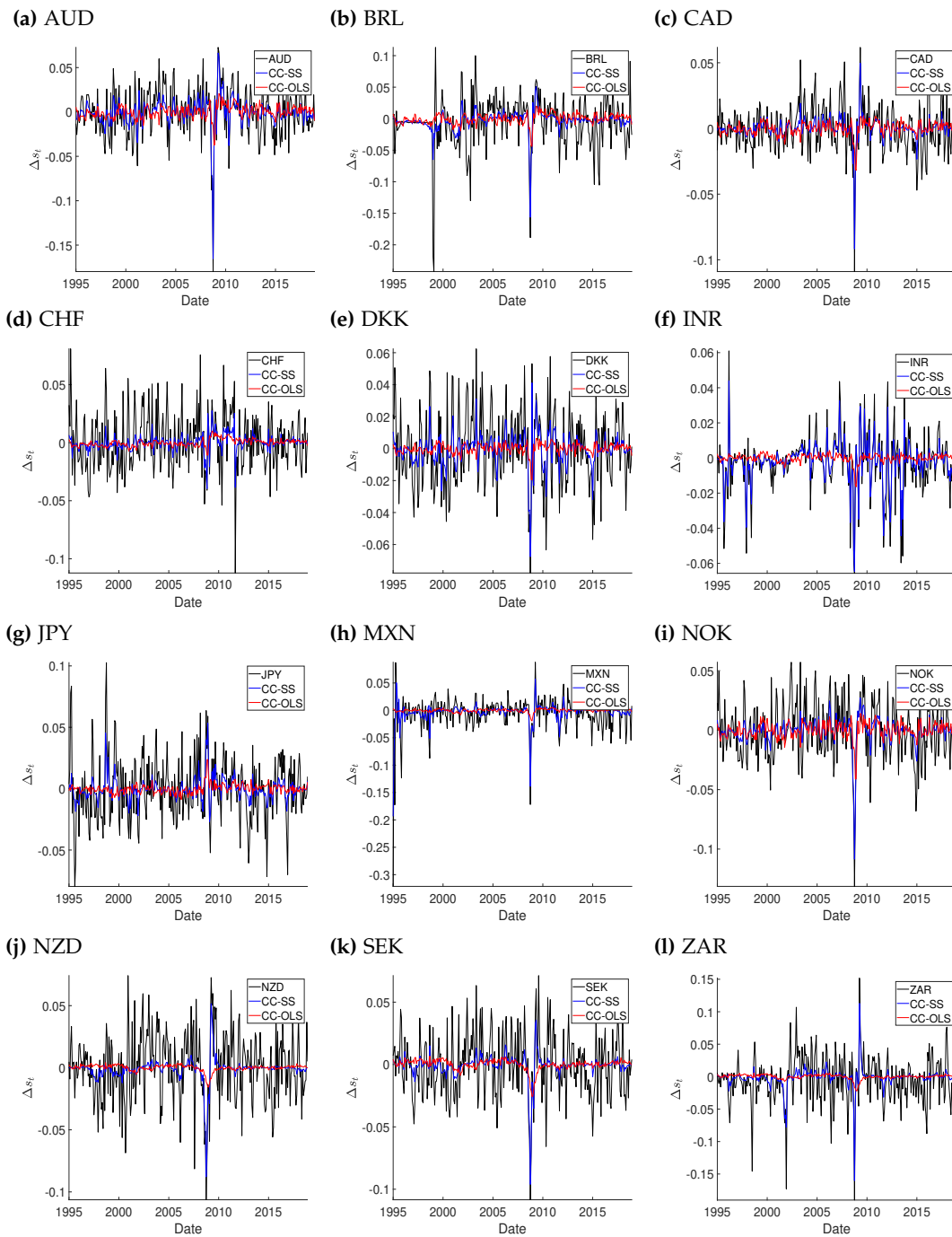
C Additional Results

Figure C-1. In-sample Fit – Real Economy Indicator



Note: The figure displays the results of a model estimated with only 1 factor, the real economy factor. The black line is the FX change, the blue line is the TVL model fit, and the red line is the OLS model fit.

Figure C-2. In-sample Fit – 3 Indicators



Note: The figure displays the results of a model estimated with 3 factors. The black line is the FX change, the blue line is the TVL model fit, and the red line is the OLS model fit.

Figure C-3. Loadings – Real Economy Indicator

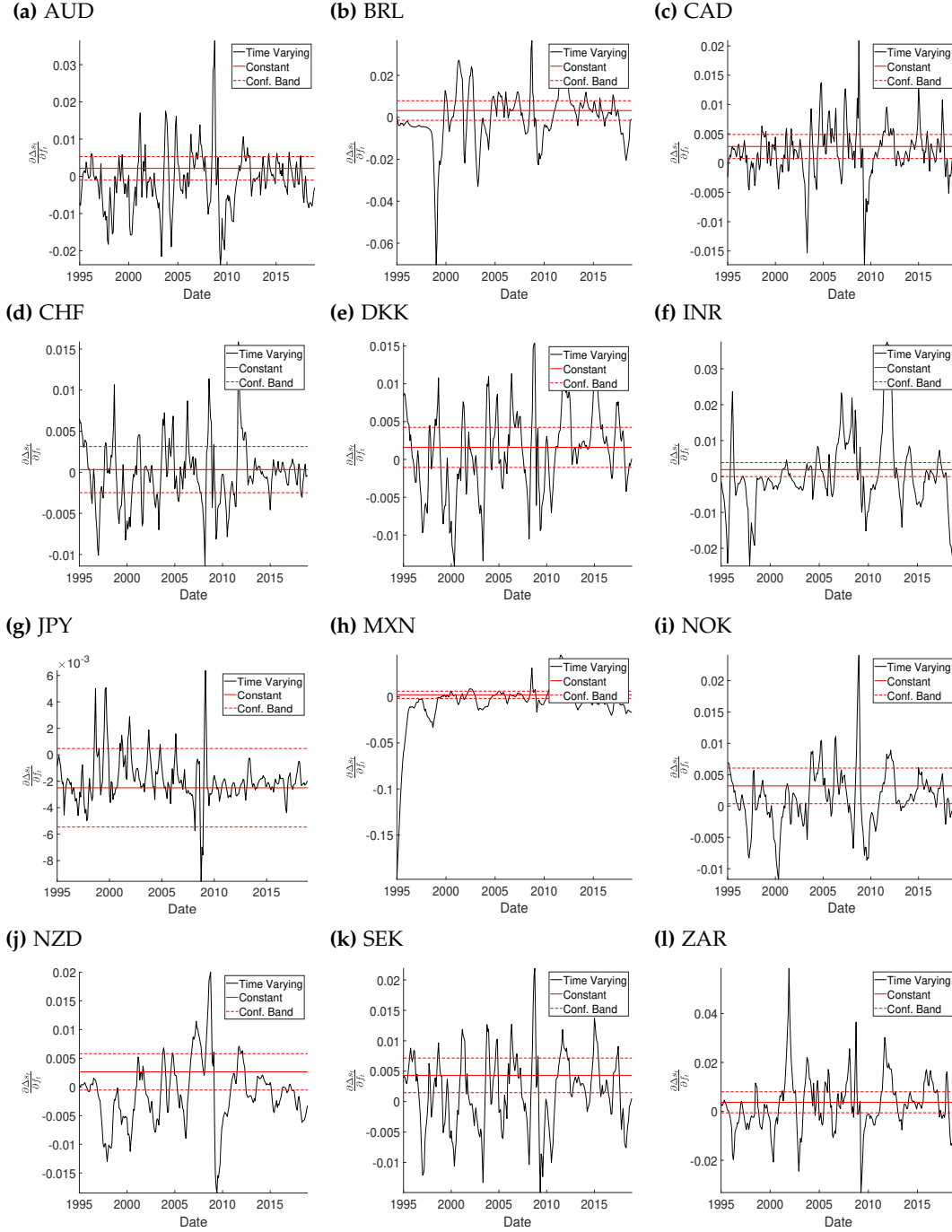
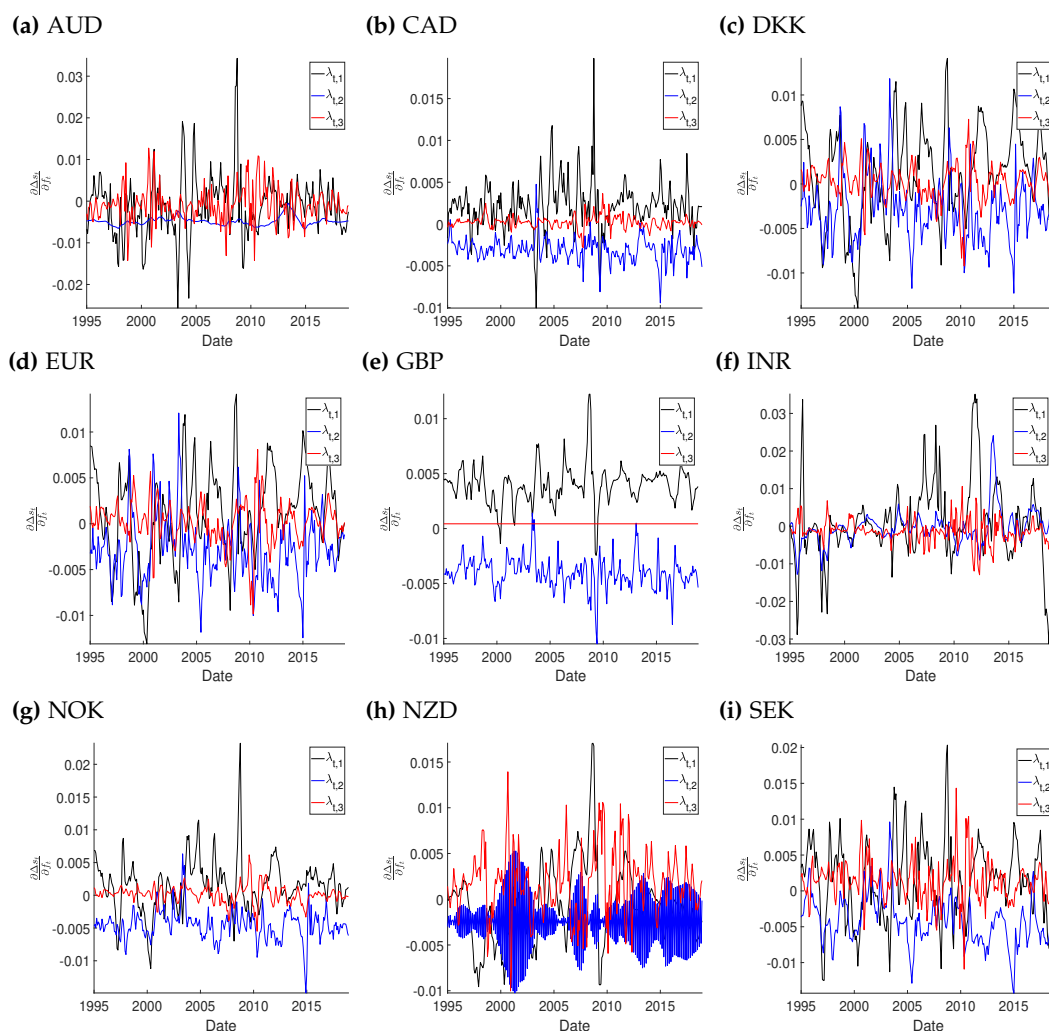


Figure C-4. Loadings – 3 Indicators



Note: The figure displays the loadings of the 3 factor model. The black line is the loading on the real economy factor, the blue line the loading on the monetary factor, and the red line the loading on the housing factor.

D Internet Appendix: Robustness Checks

D.1 5 Factor Model

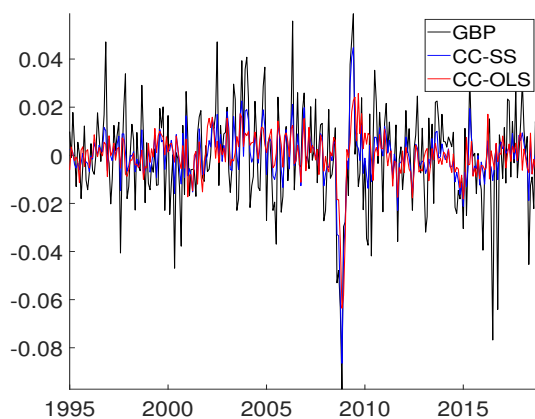
Table D-1. In-Sample Performance 5 Factor Model

Currency	R^2		Hit Rate	
	TVL	OLS	TVL	OLS
AUD	0.81	0.19	87.50	65.28
CAD	0.59	0.18	72.57	59.72
DKK	0.83	0.10	87.85	60.42
JPY	0.54	0.06	75.69	60.76
MXN	0.67	0.05	70.49	51.39
NZD	0.84	0.17	86.46	60.07
NOK	0.75	0.18	82.99	62.85
SEK	0.80	0.20	84.72	62.50
CHF	0.76	0.06	86.46	61.46
BRL	0.53	0.08	79.17	61.46
INR	0.87	0.06	87.50	58.68
ZAR	0.50	0.13	69.79	58.33
GBP	0.61	0.21	71.88	61.46
EUR	0.87	0.10	89.58	59.72

Note: The table reports measures of in-sample fit to compare the OLS and TVL model. Namely, both the squared correlations between changes in the exchange rate and the in-sample prediction of the TVP & OLS model as well as the hit rate in %. The latter being the times the sign of the fitted values corresponded to the sign of the realised values.

Figure D-1. GBP & EUR In-Sample Fit – 5 Factor Model

(a) GBP & Model Fit



(b) EUR & Model Fit

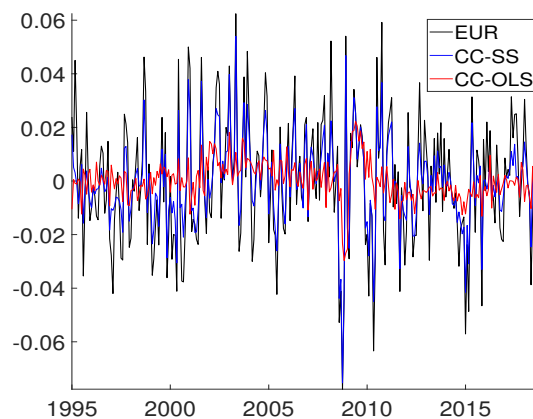


Figure D-2. In-sample Fit – 5 Factor Model

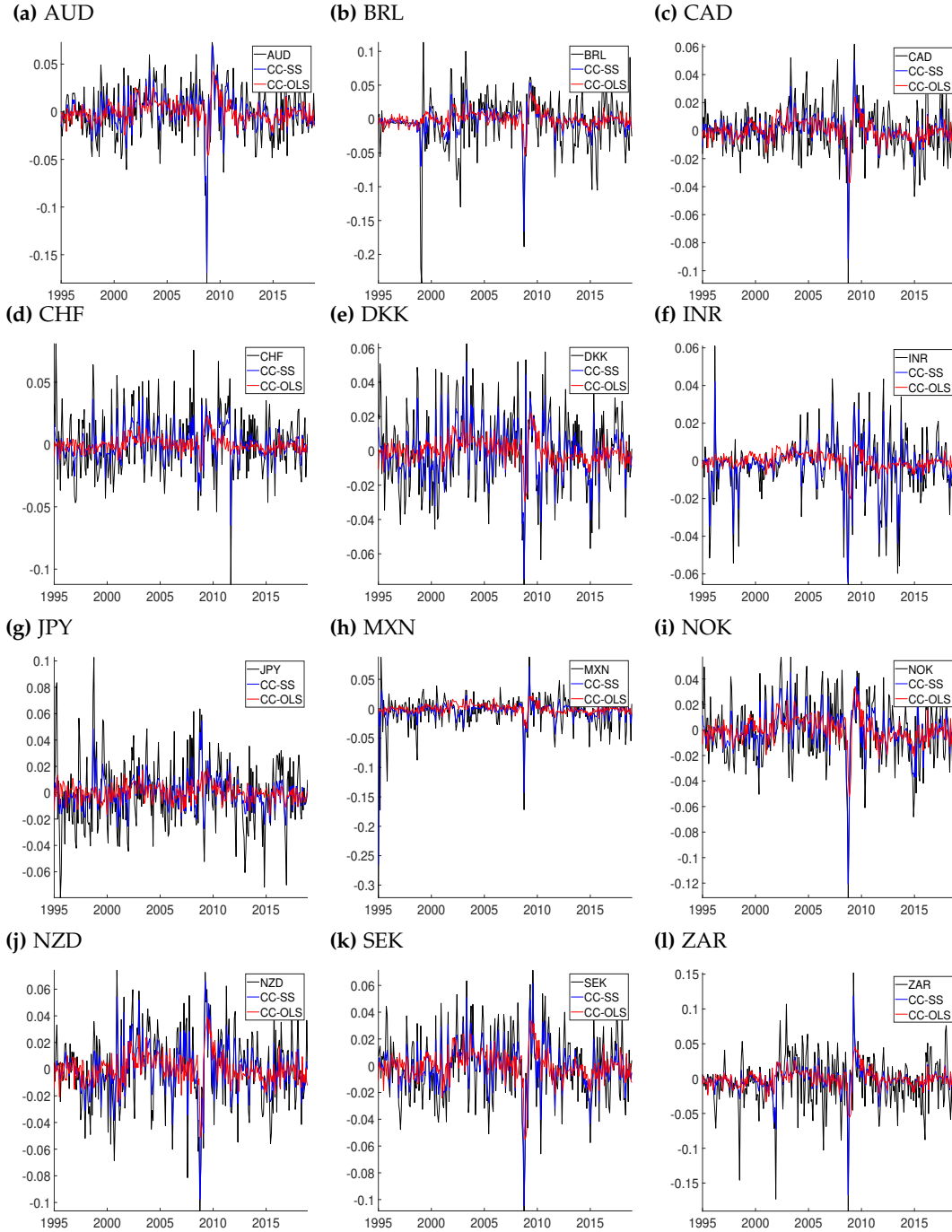


Figure D-3. Loadings – 5 Factor Model

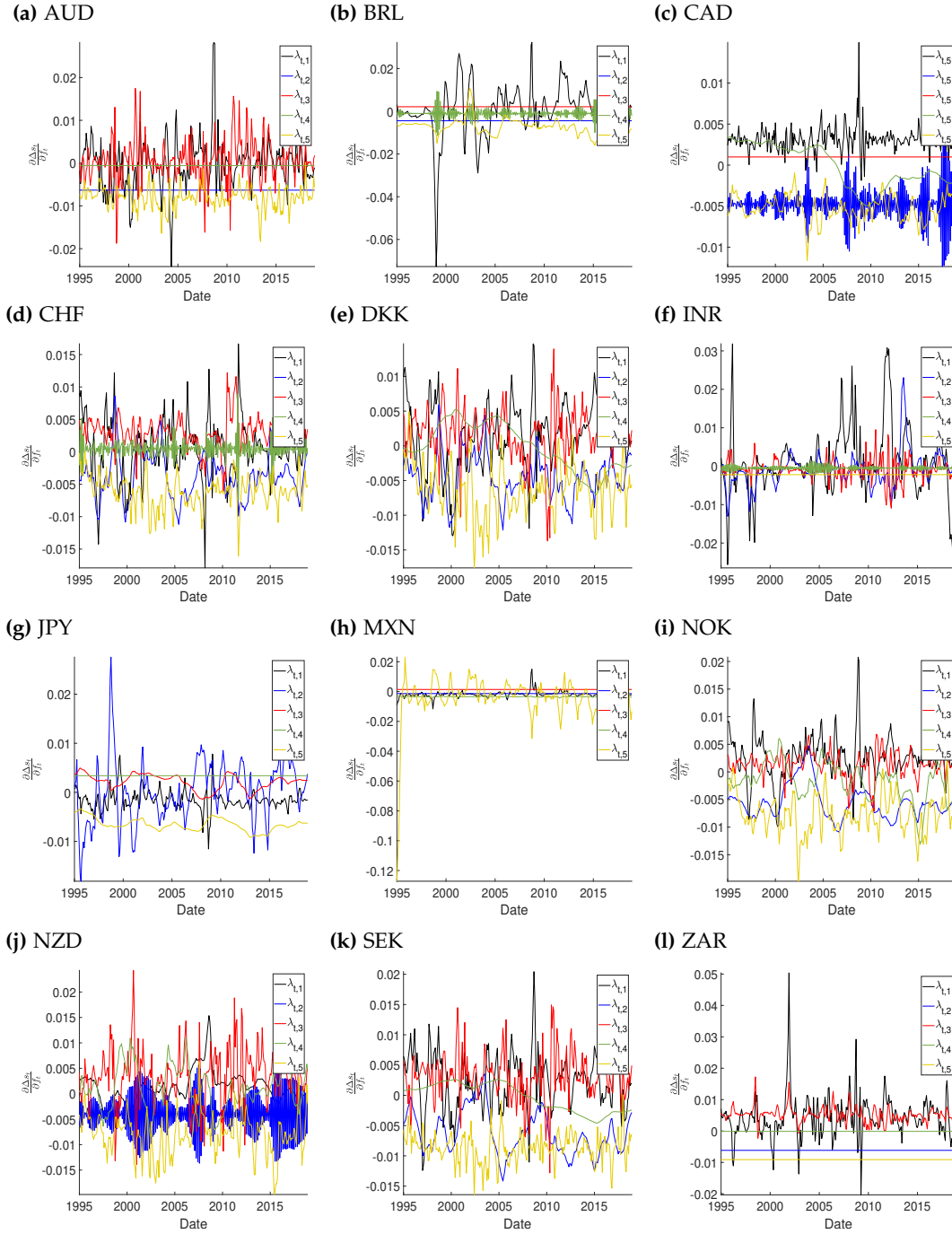
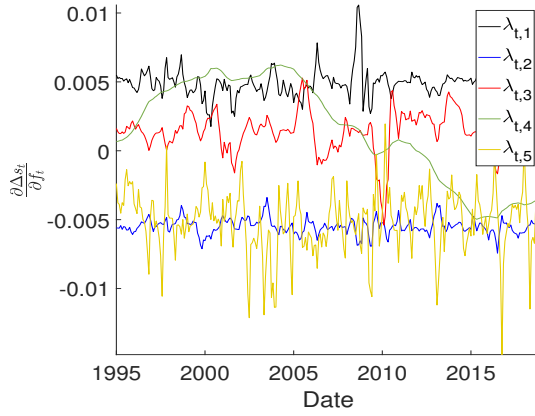
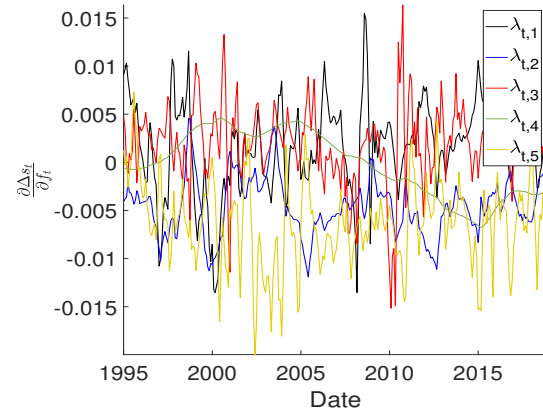


Figure D-4. GBP & EUR Loadings – 5 Factor Model

(a) GBP & Model Fit



(b) EUR & Model Fit



D.2 Forecast Robustness

Table D-2. Forecast Statistics: 1 Factor Model

Currency	RMSE			Giacomini-White				Pesaran-Timmermann			
				$\mathcal{L}$: Quadratic		$\mathcal{L}$: Absolute		TVL		OLS	
	TVL	OLS	Δ	p-val	Stat.	p-val	Stat.	p-val	Stat.	p-val.	Stat.
AUD	0.029	0.031	-	0.023**	7.541	0.047**	6.118	0.077*	1.429	0.955	-1.692
CAD	0.020	0.021	-	0.080*	5.056	0.064*	5.497	0.361	0.355	0.748	-0.669
DKK	0.022	0.023	-	0.071*	5.299	0.045**	6.192	0.218	0.777	0.961	-1.757
JPY	0.023	0.024	-	0.513	1.334	0.756	0.560	0.257	0.651	0.166	0.971
MXN	0.029	0.029	+	0.376	1.956	0.680	0.771	0.017**	2.111	0.448	0.130
NZD	0.028	0.030	-	0.179	3.442	0.099*	4.620	0.431	0.173	0.995	-2.602
NOK	0.026	0.027	-	0.019**	7.916	0.012**	8.907	0.077*	1.424	0.890	-1.226
SEK	0.025	0.026	-	0.027**	7.241	0.001***	13.267	0.004***	2.654	0.785	-0.789
CHF	0.024	0.024	+	0.343	2.138	0.520	1.309	0.732	-0.619	0.959	-1.735
BRL	0.036	0.038	-	0.105	4.506	0.107	4.465	0.371	0.328	0.996	-2.641
INR	0.020	0.020	-	0.495	1.408	0.408	1.793	0.183	0.903	0.978	-2.006
ZAR	0.037	0.039	-	0.385	1.908	0.333	2.198	0.455	0.112	0.695	-0.510
GBP	0.021	0.022	-	0.118	4.279	0.307	2.362	0.049**	1.657	0.096*	1.307
EUR	0.023	0.023	-	0.080**	5.059	0.046**	6.179	0.272	0.607	0.961	-1.757

Note: The table reports the Root Mean square Error (RMSE) of the forecasts and the sign of the difference between them. A (-) indicates that the OLS model has a greater RMSE. It also reports results of the [Giacomini and White \(2006\)](#) test for conditional predictive ability using a quadratic and an absolute loss function. The sign of the average of the quadratic loss function differential necessarily corresponds to the one of the RMSE difference. This is not necessarily true for the absolute loss function where the difference is negative for the CHF and positive for the ZAR. The test is insignificant for both, hence the table only reports the RMSE differential. Further it reports the reports of the [Pesaran and Timmermann \(1992\)](#) nonparametric direction accuracy test.

***: $p \leq 0.01$, **: $p \leq 0.05$, *: $p \leq 0.1$

Table D-3. Forecast Statistics: 3 Factor Model ($P = 100$)

Currency	RMSE			Giacomini-White				Pesaran-Timmermann			
				$\mathcal{L}$: Quadratic		$\mathcal{L}$: Absolute		TVL		OLS	
	TVL	OLS	Δ	p-val	Stat.	p-val	Stat.	p-val	Stat.	p-val.	Stat.
AUD	0.022	0.023	-	0.212	3.106	0.062*	5.563	0.085*	1.375	0.240	0.705
CAD	0.017	0.018	-	0.159	3.678	0.150	3.792	0.216	0.785	0.276	0.595
DKK	0.019	0.020	-	0.276	2.577	0.918	0.172	0.246	0.687	0.296	0.536
JPY	0.022	0.022	-	0.427	1.700	0.782	0.491	0.007***	2.445	0.162	0.986
MXN	0.027	0.027	-	0.617	0.967	0.232	2.920	0.145	1.056	0.177	0.927
NZD	0.024	0.024	+	0.718	0.662	0.908	0.194	0.757	-0.697	0.832	-0.964
NOK	0.022	0.023	-	0.068*	5.367	0.101	4.593	0.227	0.748	0.210	0.805
SEK	0.021	0.022	-	0.304	2.384	0.060*	5.623	0.253	0.665	0.711	-0.555
CHF	0.022	0.022	+	0.456	1.573	0.657	0.840	0.590	-0.226	0.700	-0.523
BRL	0.039	0.036	+	0.287	2.496	0.297	2.425	0.122	1.167	0.609	-0.277
INR	0.019	0.019	-	0.979	0.042	0.538	1.240	0.105	1.256	0.466	0.085
ZAR	0.032	0.033	-	0.021**	7.603	0.280	2.545	0.042**	1.728	0.380	0.305
GBP	0.019	0.019	-	0.787	0.479	0.599	1.026	0.024**	1.971	0.004***	2.615
EUR	0.019	0.020	-	0.196	3.257	0.831	0.369	0.328	0.446	0.394	0.268

Note: The table reports the Root Mean square Error (RMSE) of the forecasts and the sign of the difference between them. A (-) indicates that the OLS model has a greater RMSE. It also reports results of the [Giacomini and White \(2006\)](#) test for conditional predictive ability using a quadratic and an absolute loss function. The sign of the average of the quadratic loss function differential necessarily corresponds to the one of the RMSE difference. This is not necessarily true for the absolute loss function where the difference is negative for the CHF and positive for the ZAR. The test is insignificant for both, hence the table only reports the RMSE differential. Further it reports the reports of the [Pesaran and Timmermann \(1992\)](#) nonparametric direction accuracy test.

***: $p \leq 0.01$, **: $p \leq 0.05$, *: $p \leq 0.1$

Table D-4. Forecast Statistics: 3 Factor Model ($P = 180$)

Currency	RMSE			Giacomini-White				Pesaran-Timmermann			
				$\mathcal{L}$: Quadratic		$\mathcal{L}$: Absolute		TVL		OLS	
	TVL	OLS	Δ	p-val	Stat.	p-val	Stat.	p-val	Stat.	p-val.	Stat.
AUD	0.028	0.030	-	0.046**	6.168	0.138	3.958	0.076*	1.429	0.102	1.272
CAD	0.020	0.021	-	0.181	3.414	0.463	1.539	0.275	0.598	0.086*	1.364
DKK	0.023	0.023	-	0.110	4.421	0.084*	4.964	0.383	0.298	0.588	-0.221
JPY	0.051	0.023	+	0.355	2.073	0.563	1.150	0.657	-0.404	0.318	0.473
MXN	0.027	0.027	-	0.938	0.129	0.774	0.513	0.498	0.005	0.187	0.890
NZD	0.028	0.029	-	0.468	1.519	0.247	2.799	0.780	-0.773	0.580	-0.202
NOK	0.025	0.027	-	0.067*	5.409	0.109	4.425	0.106	1.246	0.159	1.000
SEK	0.026	0.026	-	0.635	0.910	0.570	1.124	0.662	-0.419	0.716	-0.570
CHF	0.024	0.024	+	0.445	1.621	0.335	2.184	0.933	-1.498	0.603	-0.262
BRL	0.038	0.037	+	0.725	0.643	0.830	0.372	0.255	0.659	0.841	-1.000
INR	0.019	0.019	+	0.591	1.050	0.749	0.579	0.641	-0.362	0.764	-0.720
ZAR	0.041	0.040	+	0.565	1.142	0.492	1.418	0.279	0.585	0.113	1.211
GBP	0.022	0.022	-	0.146	3.844	0.448	1.605	0.117	1.188	0.065*	1.518
EUR	0.044	0.023	+	0.220	3.028	0.105	4.512	0.272	0.605	0.700	-0.523

Note: The table reports the Root Mean square Error (RMSE) of the forecasts and the sign of the difference between them. A (-) indicates that the OLS model has a greater RMSE. It also reports results of the [Giacomini and White \(2006\)](#) test for conditional predictive ability using a quadratic and an absolute loss function. The sign of the average of the quadratic loss function differential necessarily corresponds to the one of the RMSE difference. This is not necessarily true for the absolute loss function where the difference is negative for the CHF and positive for the ZAR. The test is insignificant for both, hence the table only reports the RMSE differential. Further it reports the reports of the [Pesaran and Timmermann \(1992\)](#) nonparametric direction accuracy test.

***: $p \leq 0.01$, **: $p \leq 0.05$, *: $p \leq 0.1$

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