

DOCUMENTOS DE TRABAJO

Robustness in Foreign Exchange Rate Forecasting Models: Economics-Based Modelling After the Financial Crisis

Carlos Medel

Gilmour Camilleri

Hsiang-Ling Hsu

Stefan Kania

Miltiadis Touloumtzoglou

N.º 784 Mayo 2016

BANCO CENTRAL DE CHILE





BANCO CENTRAL DE CHILE

CENTRAL BANK OF CHILE

La serie Documentos de Trabajo es una publicación del Banco Central de Chile que divulga los trabajos de investigación económica realizados por profesionales de esta institución o encargados por ella a terceros. El objetivo de la serie es aportar al debate temas relevantes y presentar nuevos enfoques en el análisis de los mismos. La difusión de los Documentos de Trabajo sólo intenta facilitar el intercambio de ideas y dar a conocer investigaciones, con carácter preliminar, para su discusión y comentarios.

La publicación de los Documentos de Trabajo no está sujeta a la aprobación previa de los miembros del Consejo del Banco Central de Chile. Tanto el contenido de los Documentos de Trabajo como también los análisis y conclusiones que de ellos se deriven, son de exclusiva responsabilidad de su o sus autores y no reflejan necesariamente la opinión del Banco Central de Chile o de sus Consejeros.

The Working Papers series of the Central Bank of Chile disseminates economic research conducted by Central Bank staff or third parties under the sponsorship of the Bank. The purpose of the series is to contribute to the discussion of relevant issues and develop new analytical or empirical approaches in their analyses. The only aim of the Working Papers is to disseminate preliminary research for its discussion and comments.

Publication of Working Papers is not subject to previous approval by the members of the Board of the Central Bank. The views and conclusions presented in the papers are exclusively those of the author(s) and do not necessarily reflect the position of the Central Bank of Chile or of the Board members.

Documentos de Trabajo del Banco Central de Chile
Working Papers of the Central Bank of Chile
Agustinas 1180, Santiago, Chile
Teléfono: (56-2) 3882475; Fax: (56-2) 3882231

ROBUSTNESS IN FOREIGN EXCHANGE RATE FORECASTING MODELS: ECONOMICS-BASED MODELLING AFTER THE FINANCIAL CRISIS*

Carlos Medel
Banco Central de
Chile

Gilmour Camilleri
Ministerio de
Hacienda,
República de Malta

Hsiang-Ling Hsu
Universidad de
Nottingham

Stefan Kania
Universidad de
Nottingham

Miltiadis
Touloumtzoglou
Universidad de
Nottingham

Abstract

Exchange rates (FX) typically measures structural misalignments anticipating future short-run dynamics of key macroeconomic variables aiming to correct those misalignments with or without external intervention. The aim of this article is to analyse the out-of-sample behaviour of a bunch of statistical and economics-based models when forecasting FX for the UK, Japan, and the Euro Zone in relation to the US, emphasising the commodity prices boom of 2007-8 and the financial crisis of 2008-9. We analyse the forecasting behaviour of six economic plus three statistical models when forecasting from one up to 60-steps-ahead, comprising from 1981.1 to 2014.6. Our six economics-based models can be classified in three groups: interest rate spreads, monetary fundamentals, and purchasing power parity with global measures, covering a wide range of macroeconomic indicators. Our results indicate that there are changes of the best models when considering different time spans. In particular, interest-rate-based models tend to be better at predicting before 2008, also showing a better tracking when crisis hit. However, when considering until 2014, the models based on price differentials are more promising, but subject to heterogeneity across countries. These results are important since shed some light on what model specification use and combine when forecast facing different FX volatility.

Resumen

El tipo de cambio nominal (TCN) típicamente mide desalineamientos estructurales que anticipan la dinámica futura de corto plazo de variables macroeconómicas clave, con miras a corregir esos desalineamientos con o sin intervención externa. El propósito de este artículo es analizar el comportamiento fuera de muestra de un conjunto de modelos estadísticos y económicos al predecir el TCN del Reino Unido, Japón, y la Euro Zona con respecto al dólar estadounidense, enfatizando el auge de precios de materias primas de 2007-8 y la crisis financiera de 2008-9. Los seis modelos económicos pueden ser clasificados en tres grupos: diferenciales de tasas de interés, fundamentos monetarios, y paridad de poder de compra con medidas internacionales, cubriendo un amplio espectro de indicadores macroeconómicos. Los resultados indican un cambio en el mejor modelo al

* We would like to thank Pablo Medel, Denise Debattista, an anonymous referee, and seminar participants at the 2015 *Annual Meeting of the Chilean Economic Society* for their comments and suggestions. The views expressed in this working paper are solely those of the authors and do not necessarily reflect those of the *Economic Policy Department*, the Ministry for Finance of Malta, the Central Bank of Chile or its authorities. Any errors and omissions are the authors' own. Working Papers describe research in progress by the authors and are published to elicit comments and to further debate. Emails: cmedel@bcentral.cl, gilmour.camilleri@gov.mt, lexhh10@nottingham.ac.uk, lexsk17@nottingham.ac.uk y lexmt7@nottingham.ac.uk.

considerar diferentes ventanas de tiempo. En particular, modelos basados en tasas de interés tienden a ser mejores al predecir antes de 2008, también mostrando un mejor seguimiento durante la crisis. Sin embargo, al considerar hasta 2014, los modelos basados en diferenciales de precios se perfilan como promisorios, aunque sujetos a heterogeneidad a través de los países. Estos resultados son importantes al dar luces sobre qué especificación de los modelos utilizar y combinar al predecir el TCN con distinta volatilidad.

1 Introduction

Modern macroeconomics relies hugely on foreign exchange rate (FX) dynamics. Several trade theory foundations give a key role to FX in terms of the informational content that it provides. FX typically measures structural misalignments anticipating future short-run dynamics of key macroeconomic variables aiming to correct those misalignments with or without external intervention. Some common models are the (un-)covered interest rate parity and the purchasing power parity (PPP), or *law of one price*. This kind of models (the former developed primarily for interest rate dynamics) has a long tradition as common wisdom in macroeconomics for both its tractability and modelling convenience.

As an example, take the case of an English agent that invests a certain amount of money in the US pursuing a rate of return of i^{US} . Her principal plus return after s periods in British Sterling pounds corresponds to $\mathbb{E}_t[1 + e_{t+s}^{US/UK}]/(1 + e_t^{US/UK}) \times (1 + i_t^{US})$, where $e_i^{US/UK}$ is the FX at period i , and $\mathbb{E}[\cdot]$ is the expectations operator. Obviously, this return must equate the return that she would receive in her home country, i_t^{UK} .¹ Hence,

$$(1 + i_t^{UK}) = (1 + i_t^{US}) \times \frac{\mathbb{E}_t[1 + e_{t+s}^{US/UK}]}{(1 + e_t^{US/UK})}, \quad (1)$$

corresponding approximately to $i^{UK} = i^{US} + \Delta \mathbb{E}_t(e_{t+s})/e_t$. While this simple model has been used as an interest rates model, it is rather useful to understand the foundations of a plethora of FX economics-based models. Note that Equation 1 can be rearranged as:

$$\frac{\mathbb{E}_t[e_{t+s}]}{e_t} = i^{UK} - i^{US}. \quad (2)$$

Several theories explain the mechanics behind interest rates spreads using twists of Equation 2, especially useful for policymaking. Many interest rates models inherit the economic fundamentals to the FX variable.² There are subsequent extensions to Equation 2 coming from the theory, including more determinants or in a multivariate ensemble, as well as methodological, such as cointegration and vector error correction modelling (VECM).

Many articles make use of different versions of Equation 2 for forecasting purposes using a statistical evaluation criterion. However, it is raised the question on the purpose of those exercises. While a macroeconomic answer relies on policymaking, a financial perspective take an investing problem point of view, *i.e.* maximising utility as a function of wealth. As the focus is changed to investor's utility, the evaluation of models also makes a shift in this direction (referred henceforth as "financial evaluation"; see Granger and Pesaran, 2000, for a discussion on this matter).³ A common feature of these two kinds of analysis is the use of statistical models—mostly autoregressions—as candidate models.

Garratt and Lee (2010; henceforth GL) analyses the forecasting behaviour of several common economic and statistical models for the FX of Japan and the UK in relation to the US. A key feature is that the appropriateness of such models depends on the evaluation criteria, either statistical or financial. In particular, they find that an autoregressive (AR) model outperforms economic models when point forecast

¹Or, if i_t^{UK} is lower than the equivalent return obtained outside, then more English agents will invest abroad pursuing a higher return. At last, i_t^{UK} will raise until equating *all* foreign returns following the typical no-arbitrage condition. See Dornbusch, Fischer, and Startz (2010) for details.

²See Chapter 10—eloquently entitled "Some Useful Models"—in Blanchard and Fischer (1989) for details.

³We will refer to model categories as "statistical" and "economic-based", and to the evaluation procedures (described later) as "statistical" and "financial".

is evaluated with a statistical criterion, *i.e.* the root mean squared forecast error (RMSFE). However, financial evaluation suggests that economic models provide a higher rate of return.

In this article we analyse several extensions to GL analysis in the "first line"; this is, extensions to their models which ultimately are statistically evaluated. This is made to provide robustness to GL results, but also in regard to the out-of-sample behaviour of common models during the commodity prices boom of 2007-8 and the financial crisis of 2008-9. Hence, as GL uses a sample covering from 1981.1 to 2006.6, we extend the analysis using the same dataset until 2014.6.⁴ Besides the UK and Japan, we also include the FX of the Euro Zone with respect to the US.⁵ Unlike the data availability of GL, we consider forecasts up to 60-steps-ahead into analysis.

Our modelling extensions consist mainly of the use of different global price indices instead of just one foreign measure (the US) as used by GL in their PPP model. These changes go in the avenue of the PPP model using core inflation, the Brent oil price, and the IMF's *Primary Commodity Prices Index*. Our results suggest for the case of the UK a model based on monetary fundamentals outperform remaining candidates at every single horizon considering the GL sample span.⁶ Also, the AR model performs as the second best alternative at longer horizons. When considering our whole evaluation sample the performance is more homogeneous across the models. Again, evidence is mixed between economical and statistical models across the considered horizons.

For the case of Japan with the GL sample, a model based on the efficient market hypothesis outperforms remaining models at any horizon. When considering the whole sample, in the short run the proposed core inflation and oil price models, show the best forecasting performance from a higher than one period horizon. In the long-run, the remaining GL economics-based models also show a relatively better performance compared to the proposed models. Statistical models seem less promising in this case. Finally, for the Euro Zone, there are two models outperforming in the first evaluation sample: one based on monetary fundamentals and the AR. However, when considering the whole sample, the commodity price index model outperforms the benchmark only.

These results indicate that economics-based models are at least as good and sometimes superior than statistical models using a larger sample span. This is observed in the long run and when the variance of the dependent variable is increased. Remarkably, when considering the extended sample there is a transition of the best models towards PPP-implied models.

The rest of the article proceeds as follows. In Section 2 we briefly review the related literature. In Section 3 we fully describe the econometric setup of the forecasting exercise: the models, evaluation procedure, and dataset. In Section 4 we analyse our in-sample results with diagnostics checking as well as the out-of-sample performance. A special focus on the behaviour of forecasting errors is provided in order to assess the two aforementioned inflationary episodes. Finally, we conclude in Section 5.

⁴Melvin and Taylor (2009) as well as Molodtsova and Papell (2009) focus also on the out-of-sample behaviour of FX models during the crisis.

⁵We will refer to the Euro Zone as a country since we consider the European Monetary Union sharing a common currency, and hence, the same FX. Research on this matter is provided by Rosemberg (2000), Owen (2001), Dal Bianco, Camacho, and Pérez-Quirós (2012), Kirikos (2013), among others. Moreover, Brzeszczynski and Melvin (2006) warn on the importance of the Euro and US Dollar as they act as numeraries for many countries affecting key policy decisions.

⁶Note, however, that there are many reasons why GL figures are not exactly recovered in a replication exercise like this. These includes: different dataset vintages, different software algorithms (despite using the same estimation procedures at user level), and different decimal places-sensitive for log-likelihood function computation with breaks and data transformations.

2 A concise literature review

The FX dynamics as well as its forecasts have a long-standing tradition in macroeconomics. Some selected surveys are Taylor (1995), Sarno and Taylor (2002), Engel, Mark, and West (2007), Della Corte, Sarno, and Tsiakas (2009), Williamson (2009), and more recently, Evans (2011).

The different *statistical evaluation* of either economical or statistical models, has been analysed and used since the beginning of the literature mostly associated with Meese and Rogoff (1983). Some other articles using this methodology are MacDonald and Taylor (1994), Chinn and Meese (1995), Kim and Mo (1995), Mark (1995), Mark and Sul (2001), and Faust, Rogers, and Wright (2003), among others. Berkowitz and Giorgianni (2001) focus on the long-sample forecast accuracy; Clarida *et al.* (2003) on the information provided in the term-structure curve following the traditional Estrella and Mishkin (1996) argument; Kilian and Taylor (2003) on stressing the difficulties to beat the naive random walk (RW) forecast; and Cheung, Chinn, and García Pascual (2005) on the exploitation of the short-run adjustment to a long-run relationship in prices.

Some other articles, such as Boothe and Glassman (1987), Leitch and Tanner (1991), Pesaran and Timmermann (1995), Kandel and Stambaugh (1996), focus on the *out-of-sample evaluation of the investor problem*. This is one of the avenues analysed in GL which follows the approach of West, Edison, and Cho (1993), Barberis (2000), and Abhyankar, Sarno, and Valente (2005). More recently, Melvin, Prins, and Shand (2013) provide an overview as well as a complete exercise with after-crisis data for certain industrialised economies.

As economic models, GL use three restricted VECM of the type $\Delta \log(e_t^{i,j}) = \alpha + \lambda \nu_{t-1} + \beta' x_t + \varepsilon_t$, where ν_t and ε_t are white noises; ν_t comes from a restricted equation in levels, and $-1 < \lambda < 0$ is the long-run adjustment parameter. The variable x_t takes three different specifications, labelled *efficient market hypothesis* (EFH), *monetary fundamentals* (MF), and PPP. Multistep forecast with monthly variables are made for $h = \{1, 3, 6, 12, 24, 36, 48\}$ -steps-ahead with models estimated in a recursive sample scheme.

The financial evaluation in GL is made assuming an investor with a portfolio of two assets, one returning in domestic (US) and the other in foreign terms (either from Japan or the UK). The portfolio weights are chosen with a sample-valued simulation of the obtained forecasts maximising investor utility. Results are reported as the ratio between the (risk-averse) utility obtained with the candidate forecasts and the RW.

There are several ways to provide robustness to GL results. For instance, by allowing short sales (negative weights) to the investor, an asymmetrical utility function which penalises losses more severely, make available more assets in the portfolio, different portfolio-weighting strategy, among other financial set up. Furthermore, a richer assessment with more complex time series models, such as nonlinear models (Meese and Rose, 1991; Satchell and Timmermann, 1995), regime switching models (Engel and Hamilton, 1990; Cheung and Erlandsson, 2005), and neuronal networks (Andreou, Georgopoulos, Likothanassis, 2002), are of interest when major disruptions are experienced.⁷ As above mentioned, we assess extensions to GL analysis considering different specifications to their models. These changes go in the avenue of the PPP model using core inflation, the Brent oil price, and the IMF's *Primary Commodity Prices Index*, for a longer sample span and including the Euro Zone. Our out-of-sample evaluation is statistically only as we are concerned with the accuracy of these models in a more volatile period of time.

⁷The *direction of forecast*, *sign test*, or *hit rate*, is also worthwhile to analyse for the investor. See Cheung and Chinn (1998) for details.

3 Econometric setup

3.1 Competing models and extensions

We make use of nine forecasting models of which five comes from GL analysis. There are six economics models; three coming from GL. We also make use of a driftless RW as a benchmark. This model alongside the AR and the exponential smoothing (ES) constitutes the set of statistical models. The baseline specification of the economic models can be summarised in the following VECM:

$$\Delta \mathbf{z}_t = \mathbf{a} + \sum_{i=1}^p \mathbf{\Gamma} \Delta \mathbf{z}_{t-i} + \boldsymbol{\alpha} \boldsymbol{\beta}' \mathbf{z}_{t-1} + \mathbf{u}_t, \quad (3)$$

where \mathbf{z}_t is a vector of order two containing the $\log(e_t^{i,j})$ and $\log(x_t)$ variables. The variable x_t changes according to each model. The cointegrating vector $\boldsymbol{\beta}$ is restricted to $\boldsymbol{\beta}' = (1, -1)$.⁸ \mathbf{u}_t is a white noise; \mathbf{a} , $\mathbf{\Gamma}$, and $\boldsymbol{\alpha}$ are vector parameters to be estimated with OLS. The lag-length p is determined with the likelihood ratio sequential test using the estimation sample.

The used models are:

- **Efficient Market Hypothesis (EMH)**. In this model, the variable x_t is defined as $x_t = f_t$, where f_t is the log of the forward nominal bilateral exchange rate (end-of-period). The main reason for the use of this model relies on the information provided by the interest rate term structure curve as pointed out in Taylor (1989), Clarida and Taylor (1997), and more recently Møller (2014).
- **Monetary Fundamentals Model (MF)**. In this model, the variable x_t takes the form $x_t = (m_t - m_t^*) - (y_t - y_t^*)$, where m_t is the log-level of M1 and y_t is a measure of activity, *i.e.* industrial production. Variables with "*" indicate foreign precedence, in this case, the US. This model has a long-standing tradition in economics as a fundamental FX determination model (see Frenkel, 1976, 1979; Dornbusch, 1976; Mussa, 1976; and Hooper and Morton, 1982).
- **Purchasing Power Parity (PPP; Core; P(Oil); Cmdty)**. This model makes use of $x_t = p_t - p_t^*$, where p_t is the log of CPI. This model constitutes the law of one price, suggesting that a no-arbitrage condition holds across countries (labelled PPP).
 - We also consider $x_t = \tilde{p}_t - \tilde{p}_t^*$, where \tilde{p}_t is the so-called *core inflation* measure, *i.e.* the whole CPI excluding the components of food and energy. As this model concerns a measure more prone to policy decisions (Goodfriend, 2008), the FX trajectory should accommodate to those decisions becoming sensitive to the inner movements of the CPI. While Garratt *et al.* (2006) find evidence that PPP is fulfilled at the long run, Hakkio (2009) finds that inflationary shocks are spilled over countries even at core level. This fact, and since the PPP theory is not specific on which price level measure should be used, we opt to explore this avenue for our purposes. This model is labelled as "Core".
 - Lastly, we make use of two global prices measures in order to include a price gap beyond pairwise comparisons. These twists are made to assess the detrimental effects of two major disruptions occurred outside the sample span used in GL, which are the commodity prices boom of 2007-8 and the financial crisis of 2008-9. Hence, we define $x_t = p_t - p_t^{oil}$ and $x_t = p_t - p_t^{cmdty}$, where p_t^{oil} is the log-level of the Brent oil price and p_t^{cmdty} is the log-level of IMF's *Primary Commodity Prices* index (detailed later). These models are labelled "P(Oil)" and "Cmdty".

⁸It is analysed later to what extent this restriction find empirical support.

- **Stationary Autoregressive Model (AR).** This model corresponds to the traditional AR time series model of order p , where p is chosen according to the Akaike Information Criteria (AIC). The model assumes that $z_t = \log(e_t^{i,j})$ and $\beta' = 0$. Almost all empirical analysis and forecasting exercises of FX includes this model as either candidate or benchmark given its accurate results.
- **Exponential Smoothing Forecast (ES).** GL makes use of the RW as a benchmark forecast. Nevertheless, and as suggested in Hyndman *et al.* (2008), the single ES model could provide at least similar results than the RW. Also, the simple version used in this article enriches the exercise in a tractable manner, as it is also used in Fat and Deszi (2011). If $y_t = \Delta \log(e_t^{i,j})$ then the single univariate ES forecast (\hat{y}_t) is defined as $\hat{y}_t = \varphi y_{t-1} + (1 - \varphi)\hat{y}_{t-1}$, with $0 < \varphi \leq 1$ (the smaller is the φ , smoother is the forecast series). Note that this one-step-ahead forecast corresponds also to the multihorizon forecast as is used with the RW (if $\varphi = 1$ we obtain exactly the RW). The model can be written as a recursion depending on \hat{y}_t . Hence, it is needed an initial value of \hat{y}_t to estimate φ . This value corresponds to the average of the first $(T + 1)/2$ values of y_t , where T is the number of observations.

3.2 Model evaluation and comparison

The statistical measure used to evaluate the accuracy of point forecast is the RMSFE:

$$\text{RMSFE}_h = \left[\frac{1}{T} \sum_{t=1}^T (y_{t+h} - \hat{y}_t^h)^2 \right]^{\frac{1}{2}}, \quad (4)$$

where \hat{y}_t^h is the h -step-ahead forecast of y_{t+h} made at period t . Note that this statistic is computed given a forecasting horizon h , and hence, the difference $T - t$ is variable depending on h , *i.e.* $T = T(h)$. To make more plausible comparison with the RW, the analysed statistic corresponds to the RMSFE Ratio defined as:

$$\text{RMSFE Ratio} = \frac{\text{RMSFE}_h^{\mathcal{M}}}{\text{RMSFE}_h^{\text{RW}}}, \quad (5)$$

where $\mathcal{M} = \{\text{EMH, MF, PPP, Core, P(Oil), Cmnty, AR, ES}\}$. Hence, as the RW acts as a pivot, values greater than unity imply a worse performance of the competing model. A ratio below unity represents a "predictive gain" of $(1 - \text{RMSFE Ratio})\%$ compared to the RW.

To investigate to what extent the predictive gains are statistically significant, we make use of the unconditional t -type test of Giacomini and White (2006) providing the advantage of comparing *forecasting methods* instead of *forecasting models*. As the null hypothesis (NH) is defined as *the competing model has a superior predictive ability compared to the RW*, we use a one-side t -type GW statistic accordingly.

Formally, it is tested the $NH: \mathbb{E}_t(d_h) \leq 0$, against the alternative $AH: \mathbb{E}_t(d_h) > 0$, where:

$$d_h = (y_{t+h} - \hat{y}_t^{\text{RW}})^2 - (y_{t+h} - \hat{y}_t^{\mathcal{M}})^2, \quad (6)$$

using the Newey and West (1987) HAC estimator of the standard deviation of d_h . The NH is rejected if the subsequent t -statistic is greater than $t_{\alpha\%}$; this last term corresponds to the tabulated value of a normal distribution with probability $\alpha\%$.

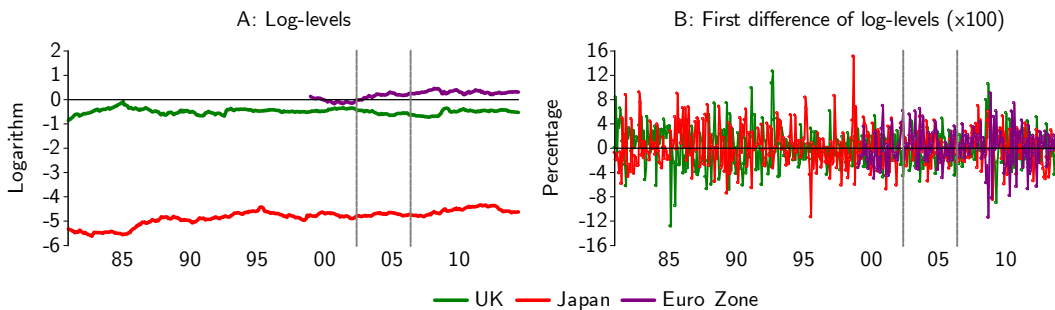
3.3 Data

The dataset comprises monthly variables from 1981.1 to 2014.6 (396 observations). Note that the GL sample cover from 1981.1 to 2006.6 (306 observations). We divide the sample into three subsamples: estimation sample, evaluation sample I (ES.I), and evaluation sample II (ES.II). The estimation sample and ES.I coincide with the division made in GL: 1981.1–2002.6 (255 observations) and 2002.7–2006.6 (51 observations), respectively. We then extend the analysis to 2014.6 (90 new observations), becoming ES.II. Our out-of-sample results are presented for these two samples to ease a direct comparison, noticing that ES.II includes ES.I. Given this scheme, we compute 144 forecasts at one-step-ahead until 85 for 60-steps-ahead. We estimate the models in a recursive manner adding one observation every time a new forecast is made.

The data sources are IMF’s *International Financial Statistics (IFS)* and OECD’s *StatsExtracts* databases. In Figure 1, we present the three dependent variables analysed; in log-levels (Panel A) and the first difference of the log-levels (Panel B; $100 \times \Delta \log(e_t^{i,j})$). Note that for the Euro Zone, the sample starts in 1999.1 (186 observations), circumscribing the analysis for this region to this sample span. Note that in Panel A, Japan exhibits always negative values indicating values smaller than unity in its FX at least over the two last decades.

In Annex A, we fully describe the sources and the specific IFS codes (when corresponding) of the dataset. Also, in Annex B we present different descriptive statistics for three different samples as well as the unit root testing results. We can observe major differences in mean, median, and variance between the two evaluation samples, obviously, increasing its volatility in the last part. The Augmented Dickey-Fuller test (ADF) is applied using the full sample to investigate the presence of a unit root, which also shed some light on the reliability of the restriction imposed in the VECM. The results suggest that in log-levels terms two variables are $I(1)$ at 10% level of confidence, and $I(0)$ in first differences. These are for the UK and Euro Zone, going in the direction that supports the restrictions. For Japan, the results suggest that the log-level is already $I(0)$ at 10% confidence. The test is conducted assuming a constant in the cointegration equation and using the Bayesian Information Criterion (BIC) as a lag-length criteria ($p^{\max}=24$).

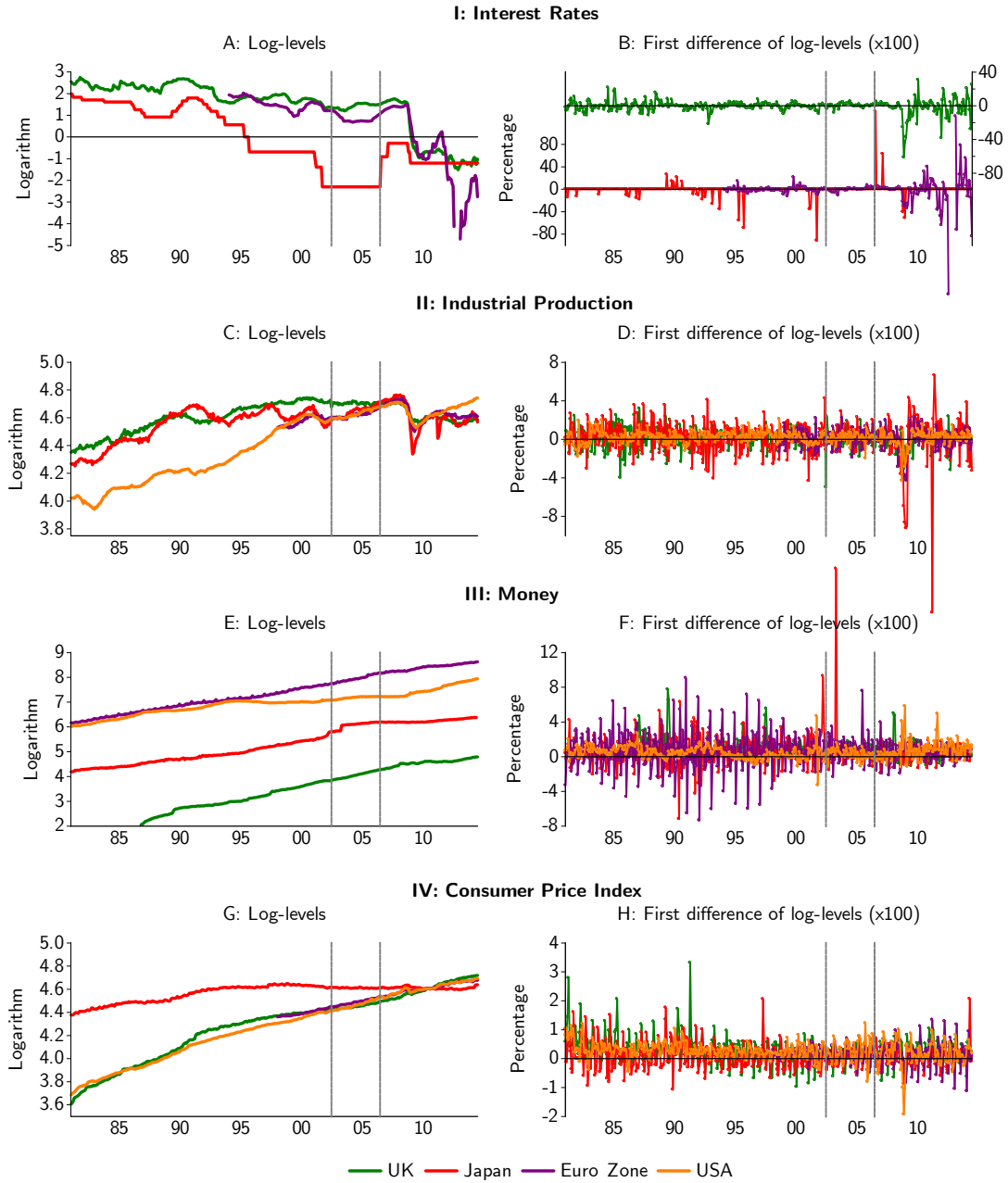
Figure 1: Foreign Exchange Rate Time Series (*)



(*) Vertical lines: Evaluation Sample I and Evaluation Sample II. Source: IFS.

In Figure 2 we present the covariates (x_t candidates) used for the baseline GL models, in the same order that models were described in Subsection 3.1. We observe in almost all the cases major disturbances especially in ES.II, which make the forecasting exercise more challenging.

Figure 2: Baseline Models Covariates Time Series (*)



(*) See notes in Figure 1. Source: IFS.

Panel I shows the interest rates series used for the EMH model (see Table A1 in the Appendix). The behaviour of the UK rate seems to follow a different regime since the half of ES.II, considering that log-levels now exhibit negative values. Also, Panel B reveals a noticeable higher variance in ES.II. A big jump is adverted for Japan at the beginning of ES.II, for sure affecting the accuracy especially in models with a greater persistence. For the Euro Zone, there are four missing observations given negative values, which do not receive any special treatment. Major disturbances are also noticed especially in the second half of ES.II.

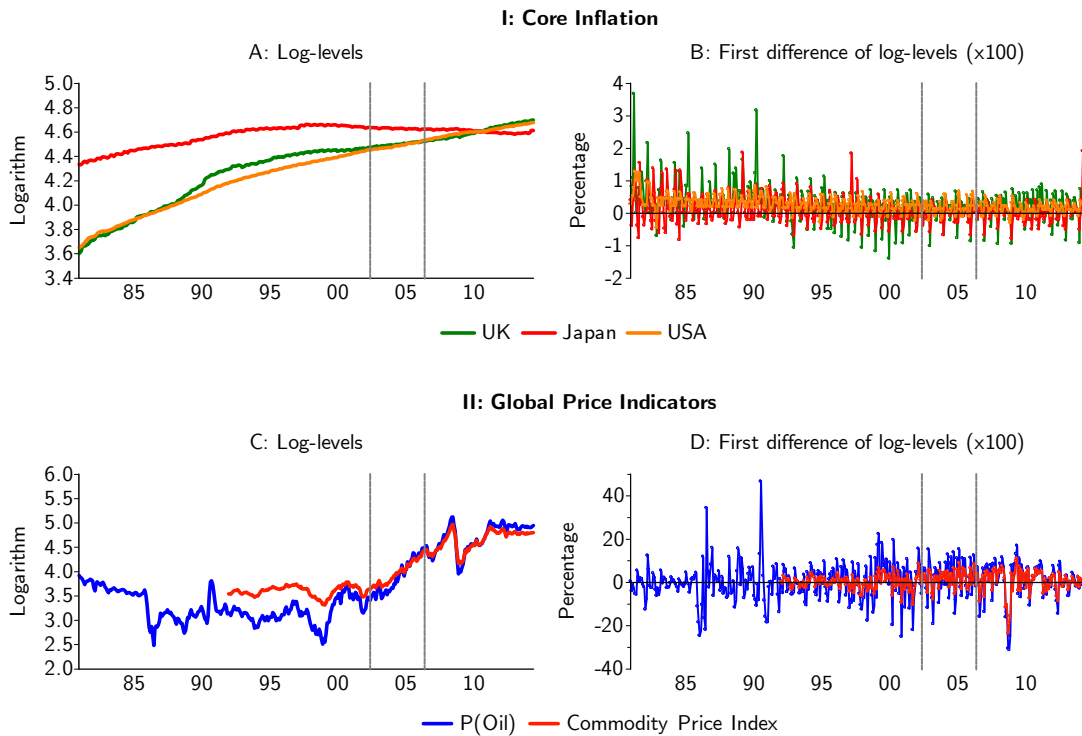
Panels II and III present the variables used for the MF model: money (M1) and industrial production. Money variables seem smooth with no major shifts for the whole sample, except of one outlier for Japan in ES.I. The industrial production series exhibit a strong correlation in the middle of ES.II, specifically corresponding to the financial crisis of 2008-9. Log-levels exhibit a typical *V*-shape dynamic except for Japan showing a *W*-shape series generating major disturbances in the first differences series accordingly.

Panel IV shows the CPI variable used for the PPP model. No major disturbances are noticed except a minor hump in ES.II for all countries which does not generate atypical observations in the first difference transformation of the series.

Overall, we have that for ES.II the covariates are more volatile, showing outliers and a regime different from the previous ES.I span (and GL analysis).

In Figure 3, we present the three variables used in the economics-based extensions: core inflation, oil price, and commodity price index.

Figure 3: Extension Models Covariates Time Series (*)



(*) See notes in Figure 1. Source: IFS and OECD.

Panel I shows core inflation for three economies: UK, Japan, and the US. There is no available official core inflation for the Euro Zone; hence we leave this model for further research. Note that as core inflation excludes the most volatile components (food and energy) the series exhibit a smooth behaviour with both transformations.

Panel II shows the oil price and the commodity price index for P(Oil) and Cmdty. The oil price corresponds to the Brent oil price defined as USD per barrel. The log-level starts to grow precisely when ES.I begins. Also, in ES.II exhibits a *V*-shape dynamic but with a growth rate close to zero in the aftermath.

The commodity price index (*IMF Primary Commodity Prices*) consists of a weighted average of food, beverages, agricultural and raw-materials, metals, and petroleum index prices using the weights of an average commodity basket estimated for 2004-9. It is available since 1992.1 onwards. Note that its dynamics follows closely that of the oil price especially since mid-2002.

4 Results

This section analyses the different in- and out-of-sample results across the countries. All the results are obtained using an *ad hoc* Eviews 8 program making use of the *VARForecast* add-in.

4.1 In-sample results

In Table 1, there are presented some diagnostic statistics for the case where the model is estimated using the restricted VECM. These results are reported for two spans: full sample (1981.1-2014.6) and estimation sample (1981.1-2002.5).

Table 1: Restricted Estimation Diagnostics (*)

	UK					Japan				
	LLhd.	R ²	$\hat{\sigma}_\epsilon^2$	AIC	BIC	LLhd.	R ²	$\hat{\sigma}_\epsilon^2$	AIC	BIC
<i>EMH: Efficient markets hypothesis</i>										
FS	859.808	0.074	0.029	-6.572	-6.075	829.427	0.052	0.031	-5.596	-5.298
ES	542.545	0.134	0.031	-7.265	-6.574	512.819	0.075	0.034	-5.714	-5.300
<i>MF: Monetary fundamentals</i>										
FS	717.060	0.034	0.028	-9.584	-9.469	831.135	0.072	0.031	-8.294	-7.836
ES	392.744	0.043	0.029	-9.737	-9.563	513.817	0.083	0.034	-8.528	-7.893
<i>PPP: Purchasing power parity</i>										
FS	855.498	0.053	0.030	-12.470	-11.973	836.603	0.086	0.031	-12.210	-11.713
ES	534.802	0.080	0.032	-12.346	-11.656	516.807	0.104	0.034	-11.987	-11.296
<i>AR: Autoregressive model</i>										
FS	846.154	0.008	0.030	-4.205	-4.195	819.357	0.004	0.032	-4.071	-4.061
ES	525.869	0.003	0.032	-4.069	-4.055	505.329	0.006	0.034	-3.910	-3.896
<i>Core: Core inflation model</i>										
FS	855.836	0.055	0.030	-12.450	-11.953	837.274	0.089	0.031	-12.789	-12.292
ES	534.826	0.080	0.032	-11.990	-11.300	517.888	0.111	0.034	-12.356	-11.666
<i>P(Oil): Oil price model</i>										
FS	849.621	0.025	0.029	-6.358	-6.219	840.898	0.105	0.031	-6.170	-5.713
ES	526.263	0.017	0.032	-6.168	-5.975	522.663	0.144	0.033	-5.982	-5.347
<i>Cmdty: Commodity price index model</i>										
FS	630.062	0.176	0.022	-8.299	-7.779	551.064	0.116	0.030	-7.605	-6.972
ES	298.158	0.216	0.020	-8.834	-7.927	232.951	0.226	0.035	-7.820	-6.709

(*) FS: Full Sample (1981.1–2014.6). ES: Estimation Sample (1981.1–2002.5). "LLhd." stands for log-likelihood function. AIC and BIC stand for Akaike and Bayesian Information Criteria. Source: Authors' elaboration.

Table 2: Restricted Estimation Diagnostics (*)

Euro Zone					
	LLhd.	R^2	$\hat{\sigma}_\varepsilon^2$	AIC	BIC
<i>EMH: Efficient markets hypothesis</i>					
FS	368.666	0.011	0.030	-4.394	-4.287
ES	85.842	0.050	0.028	-7.294	-7.038
<i>MF: Monetary fundamentals</i>					
FS	385.474	0.016	0.030	-9.282	-9.177
ES	85.942	0.055	0.028	-9.543	-9.287
<i>PPP: Purchasing power parity</i>					
FS	384.595	0.007	0.030	-12.189	-12.084
ES	86.256	0.070	0.028	-13.037	-12.781
<i>AR: Autoregressive model</i>					
FS	384.045	0.001	0.030	-4.153	-4.118
ES	86.843	0.092	0.028	-4.242	-4.158
<i>Core: Core inflation model</i>					
FS					
ES					
<i>P(Oil): Oil price model</i>					
FS	384.277	0.003	0.030	-6.242	-6.137
ES	85.982	0.056	0.028	-5.897	-5.641
<i>Cmdty: Commodity price index model</i>					
FS	384.523	0.006	0.030	-7.561	-7.456
ES	85.860	0.051	0.028	-7.777	-7.521

(*) See notes in Table 1. In this case, FS spans from 1999.1 to 2014.6.

Source: Authors' elaboration.

For the UK, there are just two models that exhibit a greater R^2 when considering the whole sample: the AR and P(Oil). Note that in the case of the AR, the R^2 level as well as the increment are marginal: from 0.003 to 0.008 (0.017 to 0.025 for P(Oil) model). Given the no-arbitrage condition assumed to FX returns, it is expected a close to white noise behaviour of these series. Hence, goodness-of-fit coefficients of the mentioned size are certainly expected.

The Cmdty model exhibit for both samples the best adjustment according to this measure. When considering jointly the fit to data given by the log-likelihood function and the number of coefficients of the model (*i.e.* the information criteria), the best adjustment is achieved with the PPP model for both spans. Hence, UK FX dynamics seems to be commanded mostly by external global price indices.

For Japan, all models exhibit a lower explanatory power when considering the last part of the sample according to the R^2 statistic. In this case, the proposed three economic models exhibit a better adjustment than the baseline GL models. When considering information criteria, the Core model exhibits the best in-sample fit outperforming within economic models.

For the Euro Zone (in Table 2), all the models also show a decline in their fit when considering the last part of the sample. In this case, the proposed economics model shows a narrow fit according to the R^2 . There is not a single model showing the best results with both samples. However, the MF, PPP, and AR seem promising. Finally, according to information criteria, the best model is PPP.

Overall, we have that economic models based on price differentials provide a better in-sample fit, barely superior to the AR model. Interestingly, the latter model is also superior to the EMH which contains a forward-looking variable as the forward exchange rate interest rate. It is suitable at this point to remark that given the presence of breaks and regime changes that the in-sample performance is not necessarily extrapolated to out-of-sample accuracy (see Hansen, 2009, for a formal discussion). Obviously, it is necessary to have an estimated model closest to the true model to generate the forecasts.

We analyse next the appropriateness of the imposed restriction on the cointegrating vector. Same as before, this analysis should complement the modelling mechanism behind the results, but in spite of their acceptance or economical motivation, it should be judged by its forecasting accuracy.

In Table 3, we present the results of the Engle-Granger cointegration test. Note that we present the results for two samples just for robustness purposes, because it is desirable for consistency and testing-power-enhancing the use of a *large* sample. Hence, our results under the column "FS" will determine to what extent the log-levels are cointegrated for each model.

Our estimates consist of a residual-based testing of cointegration. If the series are not cointegrated, all linear combinations between the independent and dependent variables deliver nonstationary residuals. Hence, the *NH* of this test is *no cointegration*. The equation used for residual unit root testing is:

$$\Delta v_{1,t} = (\rho - 1)v_{1,t-1} + \sum_{j=1}^p \delta_j \Delta v_{1,t-j} + \xi_t, \quad (7)$$

where $\Delta v_{1,t}$ are the first row of residuals of the log-level regression $\mathbf{z}_t = \boldsymbol{\omega}_0 + \boldsymbol{\omega}'_1 \mathbf{z}_{t-1} + \mathbf{v}_t$; ρ and δ_j are parameters to be estimated, and ξ_t is assumed to be a white noise. We consider two statistics: a *t*-type statistic based on the hypothesis of nonstationarity ($\rho=1$), and the other based on the normalised autocorrelation coefficient $\hat{\rho} - 1$. These statistics are labelled $\hat{\tau}$ and \hat{z} and corresponds to:

$$\hat{\tau} = \frac{\hat{\rho} - 1}{\hat{\sigma}_{\hat{\rho}}}, \text{ and } \hat{z} = \frac{T(\hat{\rho} - 1)}{1 - \sum_j \hat{\delta}_j}. \quad (8)$$

That the variables show cointegration implies the existence—at least, statistically—of a long-run relationship between the variables (the cointegration vector). The model is hence defined for the FX misalignment between the short-run and the mentioned long-run relationship. This specification has the advantage that holds the information jointly of both the level and the first difference of the series. If the test rejects the existence of a cointegration vector, then the model is commanded fully by short-run dynamics without considering series level explicitly. Note that this implication while carrying important economic consequences must be judged in terms of forecasting accuracy for the purposes of this article.

The results for the case of the UK suggest that for all the models, except *Cmdty*, the variables are cointegrated at a confidence level of 5%. When cointegrated, just the *MF* model does it and with the full sample only—or at the non-conventional 13.7% level of confidence with the short sample. The rest of models are cointegrated even with the short sample. Note that the estimation of ρ seems to be surrounding 0.95 for all the models including *Cmdty*.

For the case of Japan, the result of no cointegration should not be surprising since previous unit root results suggest (Annex 2) that variables are already $I(0)$. Hence, in this case the assumption of a restricted cointegration vector would not play any role since *VECM*'s adjustment coefficient is (and should be) zero, and the model is driven by short-run dynamics.

Table 3: Engle-Granger Cointegration Analysis (*)

Dependent variable: $\log(c_t^{i,j})$		UK		Japan		Euro Zone	
		FS	ES	FS	ES	FS	ES
EMH	τ -statistic	-3.797	-3.565	-1.614	-1.334	-1.349	-2.508
	p -value	0.015	0.029	0.717	0.821	0.816	0.284
	z -statistic	-20.290	-17.182	-4.963	-3.429	-4.067	-17.478
	p -value	0.050	0.094	0.734	0.850	0.803	0.075
	$\hat{\rho}-1$	-0.051	-0.056	-0.012	-0.011	-0.023	-0.144
	$\hat{\sigma}_{\hat{\rho}}$	0.013	0.016	0.008	0.008	0.017	0.057
MF	τ -statistic	-3.457	-2.911	-1.682	-1.482	-2.947	-2.228
	p -value	0.039	0.137	0.687	0.770	0.128	0.414
	z -statistic	-23.113	-15.436	-4.236	-3.116	-14.927	-6.093
	p -value	0.027	0.131	0.791	0.870	0.142	0.634
	$\hat{\rho}-1$	-0.059	-0.065	-0.011	-0.010	-0.081	-0.068
	$\hat{\sigma}_{\hat{\rho}}$	0.017	0.022	0.006	0.007	0.027	0.031
PPP	τ -statistic	-3.621	-3.510	-1.897	-1.262	-3.361	-1.570
	p -value	0.025	0.034	0.582	0.842	0.051	0.736
	z -statistic	-20.089	-17.033	-7.619	-3.948	-19.939	-3.932
	p -value	0.052	0.096	0.522	0.813	0.050	0.812
	$\hat{\rho}-1$	-0.050	-0.056	-0.017	-0.013	-0.108	-0.044
	$\hat{\sigma}_{\hat{\rho}}$	0.014	0.016	0.009	0.010	0.032	0.028
Core	τ -statistic	-3.825	-3.753	-1.667	-1.375	-2.460	-3.651
	p -value	0.014	0.017	0.694	0.808	0.301	0.027
	z -statistic	-20.411	-17.911	-6.115	-4.452	-12.211	-23.133
	p -value	0.049	0.081	0.641	0.774	0.239	0.020
	$\hat{\rho}-1$	-0.051	-0.059	-0.015	-0.015	-0.066	-0.260
	$\hat{\sigma}_{\hat{\rho}}$	0.013	0.016	0.009	0.011	0.027	0.071
P(Oil)	τ -statistic	-3.732	-3.488	-1.933	-1.203	-3.281	-2.292
	p -value	0.018	0.036	0.563	0.858	0.062	0.383
	z -statistic	-20.153	-16.982	-4.820	-3.755	-15.179	-6.100
	p -value	0.052	0.097	0.746	0.827	0.135	0.633
	$\hat{\rho}-1$	-0.050	-0.056	-0.011	-0.010	-0.082	-0.069
	$\hat{\sigma}_{\hat{\rho}}$	0.013	0.016	0.006	0.009	0.025	0.030
Cmdty	τ -statistic	-2.570	-2.781	-2.744	-2.191	-2.849	-2.106
	p -value	0.253	0.177	0.188	0.431	0.156	0.476
	z -statistic	-12.115	-13.680	-14.892	-9.240	-13.070	-5.694
	p -value	0.247	0.181	0.146	0.401	0.204	0.668
	$\hat{\rho}-1$	-0.045	-0.079	-0.047	-0.053	-0.071	-0.064
	$\hat{\sigma}_{\hat{\rho}}$	0.018	0.028	0.017	0.024	0.025	0.030

(*) FS: Full Sample. ES: Estimation Sample. *NH*: Series are not cointegrated.

Cointegration equation deterministics: Constant. MacKinnon (1996) one-sided

p -values. Highlighted cells: p -value>10%. Source: Authors' elaboration.

For the case of the Euro Zone, we find evidence of cointegration with the PPP and P(Oil) models, and for Core model just with the estimation sample. For both cases, PPP and P(Oil), the estimation of ρ is around 0.90. In these two cases the restriction on β will have a role as in both ensembles log-levels cointegrate.

Overall, we find a strong evidence of cointegration with the UK dataset, a weaker cointegration with Euro Zone models, and no cointegration with Japanese time series.

4.2 Out-of-sample results

These results comprise two kinds of analysis for each country: the RMSFE Ratio with statistical inference (for the two sample spans, ES.I-II), and the behaviour of forecast errors across time. Lastly, we present the out-of-sample results in a compacted manner given the difficulty to achieve a unique conclusion for all countries.

4.2.1 United Kingdom

The RMSFE results for the UK are presented in Table 4. It shows that the best model in ES.I is MF model for all the horizons. The rest of the models are not superior to the benchmark. The MF model shows predictive gains ranging from 1.2 at $h=1$ to 30.2% at $h=60$. The benchmark could, in principle, be improved for $h=24$ as the RMSFE (last column of Table 4) is greater for this horizon rather than the next one (11.799 versus 11.711), as evidence of forecast inefficiency.

Table 4: UK. RMSFE Ratio Estimates (*)

	EMH	MF	PPP	AR	ES	Core	P(Oil)	Cmdty	RW
<i>Evaluation Sample I: 2002.6–2006.6</i>									
$h=1$	1.000	0.988	1.086	1.004	1.140	1.084 [†]	1.003	1.068	2.407
$h=3$	1.036	0.955	1.120 [†]	1.006	1.052	1.128 [†]	1.003	1.143 [†]	3.945
$h=6$	1.062 [†]	0.977	1.236 [†]	1.002	1.019	1.202 [†]	1.016	1.171 [†]	6.273
$h=12$	1.104 [†]	0.973	1.367 [†]	1.000	1.036	1.295 [†]	1.009	1.105	8.008
$h=24$	1.235 [†]	0.934 [†]	1.620 [†]	0.997	1.043 [†]	1.520 [†]	1.051 [†]	1.189 [†]	11.799
$h=36$	1.434 [†]	0.847 [†]	2.010 [†]	0.996	1.068 [†]	1.888 [†]	1.090	1.312 [†]	11.711
$h=48$	1.403 [†]	0.798	1.886	0.983	1.152	1.843 [†]	1.080	1.323	17.102
<i>Evaluation Sample II: 2002.6–2014.6</i>									
$h=1$	1.136	1.007	1.050	0.993	1.277	1.038	0.990	1.000	2.574
$h=3$	1.202	0.999	1.021	0.992	1.114	1.024	0.994	0.975	4.985
$h=6$	1.172	1.007	1.046	1.001	1.011	1.053	1.043	0.970	8.404
$h=12$	1.127	1.014	1.066	1.002	1.000	1.068	1.041	1.006	10.161
$h=24$	1.106	1.029	1.119	1.001	1.000	1.012	1.024	1.042	13.489
$h=36$	1.081	1.067	1.134	1.001	1.003	1.117	1.028	1.052	13.728
$h=48$	1.045	1.088	1.106	1.001	0.998	1.084	1.040	1.085	17.093
$h=60$	0.991	1.138	1.012	1.000	0.999	1.000	1.052	1.102	19.058

(*) Figures below unity imply a worst RW performance. For RW it is presented the RMSFE. (†) GW-test null hypothesis rejected at 10% of confidence level.

Shaded cells indicate RMSFE Ratio < 1. Source: Authors' elaboration.

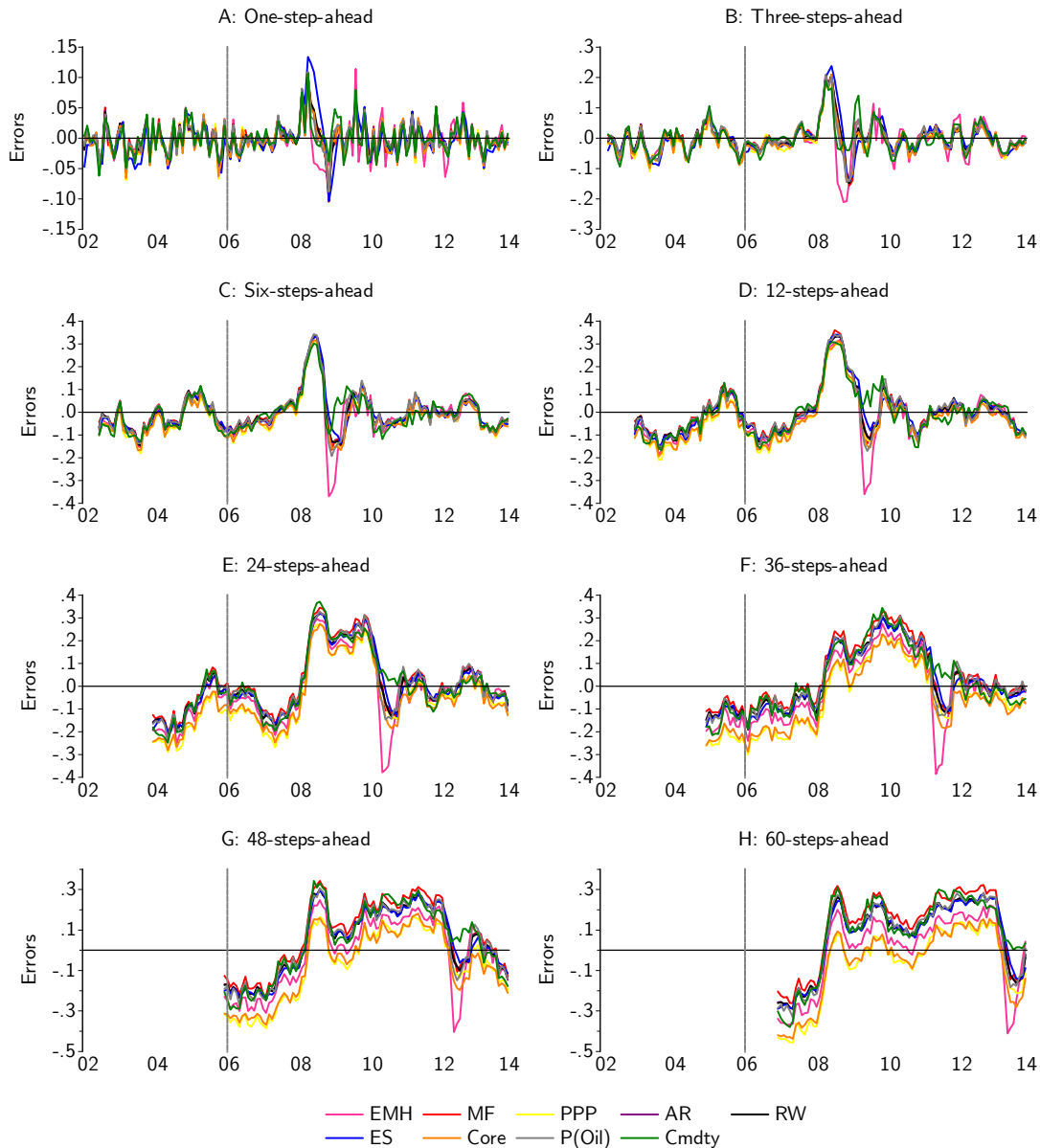
When considering ES.II, there is no unique model outperforming at every single horizon. Instead, the AR and P(Oil), plus MF and Cmdty are the best at $h=1$ and 2, and $h=2$ and 3, respectively. Then, just since $h \geq 48$, one of the competing model beats the RW, the ES, for $h=48$ and 60, and the EMH at $h=60$ only. Statistical inference favouring a competing model is found just for MF at $h=24$ and 36 using ES.I.

The forecasting errors across time for all the models and horizons are depicted in Figure 4. It is easy to notice that the FX disruption observed in 2008 was unpredictable for the UK. The forecast accuracy of

all models seems similar from $h=1$ to 24, except for the EMH model when adapting to the two known breaks in the sample; same for the ES model but at $h=1$ only.

For the remaining horizons, the same performance of EMH is noticed. But more importantly, the PPP model shows the best performance during the disruption time, in a scenario in which all the models underpredict the FX. The PPP behaviour is particularly better at $h=60$, when a few observations even overpredict the FX during the crisis. This fact, while may not be desirable from the perspective of an investor, it is an important feature in terms of accuracy, unbiasedness, and variance. As the Core model follows closely the PPP model, the same performance is noticed for the former, outperforming the remaining models during the crisis.

Figure 4: UK. Forecasting Errors across Evaluation Sample (*)



(*) Vertical line: ES.I end and ES.II start point. Source: Authors' evaluation.

4.2.2 Japan

The RMSFE results for Japan are presented in Table 5. When analysing the ES.I, the results suggest an astonishing performance of the EMF model, showing important predictive gains greater than 35% at $h=36$ and 60. For shorter horizons, the predictive gains oscillate between 1 and 9%. Note that in this case, the RMSFE profile of the RW model is specially inefficient at 24-months-ahead, describing clearly an nonadaptive forecasting behaviour of a hump. At $h=12$, the PPP, Core, and P(Oil) are also superior than the benchmark. Finally, at $h=48$ and 60 the AR model and specially the Core model show important predictive gains.

When considering ES.II, many of the models are superior to the RW since $h \geq 3$. Overall horizons, the best model is Core, showing predictive gains since $h \geq 3$, but beaten by the EMH and MF at $h=60$. Since $h \geq 6$, the P(Oil) model shows also important reductions in the RMSFE. Then, from $h \geq 24$ the EMH and MF models begin to outperform the RW. Both statistical models, AR and ES, are always close to the RW with ratios above or below unity.

Table 5: Japan. RMSFE Ratio Estimates (*)

	EMH	MF	PPP	AR	ES	Core	P(Oil)	Cmdty	RW
<i>Evaluation Sample I: 2002.6–2006.6</i>									
$h=1$	0.992	1.072	1.026	1.016	1.135	1.044 [†]	1.012	1.221	2.200
$h=3$	0.983	1.209	1.067 [†]	1.000	1.071	1.048 [†]	1.031	1.308	3.644
$h=6$	0.995 [†]	1.229	1.082 [†]	1.005	1.000	1.039 [†]	1.012	1.218 [†]	5.908
$h=12$	0.995 [†]	1.102	0.980 [†]	1.004	1.000	0.977 [†]	0.957	1.102	7.543
$h=24$	0.913 [†]	1.252 [†]	1.047 [†]	1.001	1.008	1.210 [†]	1.033 [†]	1.194 [†]	9.493
$h=36$	0.650 [†]	1.783 [†]	0.687 [†]	0.995	1.127 [†]	1.146 [†]	0.943 [†]	1.657 [†]	4.814
$h=48$	0.320 [†]	1.933	1.134 [†]	0.956	1.571 [†]	0.413 [†]	1.002	2.060	4.079
<i>Evaluation Sample II: 2002.6–2014.6</i>									
$h=1$	1.045	1.031	1.019	1.002	1.203 [†]	1.018	1.046	1.118 [†]	2.627
$h=3$	1.048	1.028	1.013	0.999	1.067	0.969	1.001	1.134 [†]	4.843
$h=6$	1.053	1.021	1.003	1.002	1.018	0.937 [†]	0.977	1.066	7.474
$h=12$	1.026	1.000	1.012	0.999	1.039 [†]	0.944 [†]	0.977	1.036	10.137
$h=24$	0.951	1.026	0.971	0.999	1.013	0.985	0.985	1.061	15.641
$h=36$	0.861 [†]	0.962	0.966	1.000	1.005	0.973	0.957	1.051	18.299
$h=48$	0.754 [†]	0.847 [†]	0.934	1.000	1.005	0.893	0.896 [†]	1.021	21.156
$h=60$	0.682 [†]	0.736 [†]	0.862 [†]	1.000	0.999	0.789 [†]	0.819 [†]	0.998	24.219

(*) See notes in Table 4. Source: Authors' elaboration.

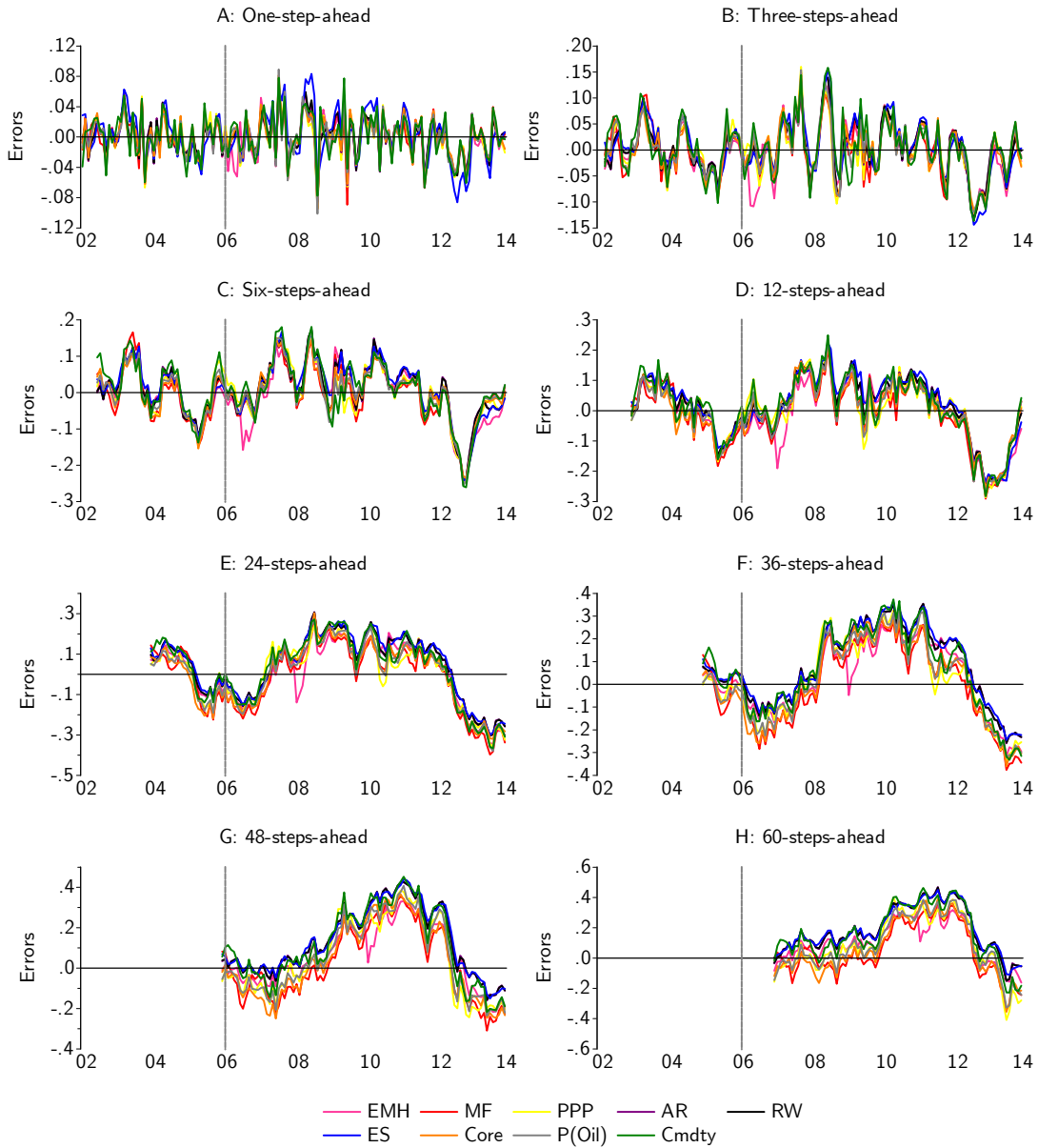
Statistical inference suggests that with ES.I, there are significant gains with the EMH model at long-run horizons; same with Core model. When considering ES.II, at long horizons we find also significant differences favouring economics models. At intermediate horizons, only the Core model exhibit statistically significant gains at 10%.

The forecasting errors across the time are depicted in Figure 5. From $h=1$ to 12-steps-ahead the errors seems following a white noise behaviour with all models, reflecting a desirable efficiency characteristic. At $h=1$ the ES model tends to exaggerate the dynamics of the series delivering forecast errors greater than the remaining models. At $h=6$ and 12, the EMH model overpredict the Japanese FX dynamics during 2007, and at the end of the sample. At short-run, there is no identifiable best or worst model. When predicting at long run, there is a noticeable positive error bias. Two models exhibit an overprediction of FX at $h=24$ and 36: EMH and PPP. For $h=48$ and 60, the EMH (again) plus the MF model captures in several observations best FX dynamics during the crisis.

4.2.3 Euro Zone

The RMSFE results for the Euro Zone are exhibited in Table 6. With ES.I there are two models that outperform the RW: MF and AR. For both this behaviour is observed for $h > 3$. At $h=12$ the EMH and PPP at $h=48$ also show a superior performance compared to the RW. When considering ES.II the AR model shows more accurate predictions at $h=24, 48,$ and 60 . However, the P(Oil) model is consistently superior than the AR (and the RW) since $h \geq 12$. Note that in only one case (ES.I and $h=48$: PPP) the predictive gains are statistically significant in favour of the candidate model. No significant gains are obtained with the ES.II.

Figure 5: Japan. Forecasting Errors across Evaluation Sample (*)



(*) See notes in Figure 4. Source: Authors' evaluation.

The forecast errors across time are presented in Figure 6. In the short run, there is an overprediction outlier of FX in mid-2008 that shared across all the models. At $h=6$ and 12, there is a W -shape dynamics due in part to an expected weak European economy in 2010 that finished with the ECB announcement of a raise in the interest rate in October 2011. The results for longer horizons exhibit an unclear bias, reflecting the lower variability obtained for statistical inference. It is remarkable, however, that the PPP model shows more volatile errors and exaggerating the dynamics of FX, whereas EMH model follows FX closely. The ES, P(Oil), and Cmdty models appear as a good alternative when predicting at the long-run. Also, the model that cast better during crisis is Cmdty.

Table 6: Euro Zone. RMSFE Ratio Estimates (*)

	EMH	MF	PPP	AR	ES	Core	P(Oil)	Cmdty	RW
<i>Evaluation Sample I: 2002.6–2006.6</i>									
$h=1$	1.035	1.040	1.064	1.032	1.230 [†]		1.039	1.042	2.626
$h=3$	1.023	1.017	1.081 [†]	1.018	1.087 [†]		1.033	1.032	4.961
$h=6$	1.009	0.992	1.111	0.995	1.046		1.023	1.011	7.954
$h=12$	0.998	0.996	1.139 [†]	0.982	1.069		1.018	1.002	9.870
$h=24$	1.041	0.980	1.105	0.979	1.066 [†]		1.061	1.022	14.845
$h=36$	1.106	0.938	1.066	0.970 [†]	1.097 [†]		1.113	1.064	15.375
$h=48$	1.201	0.960	0.834 [†]	0.962	1.112		1.133	1.176	25.466
<i>Evaluation Sample II: 2002.6–2014.6</i>									
$h=1$	1.032	1.025 [†]	1.044 [†]	1.020	1.144 [†]		1.031	1.033	3.042
$h=3$	1.034	1.010	1.064 [†]	1.005	1.079 [†]		1.010	1.011	5.112
$h=6$	1.043	1.009	1.106 [†]	1.003	1.009		1.005	1.003	8.283
$h=12$	1.052	1.016	1.178 [†]	1.003	0.987		1.004	0.999	9.689
$h=24$	1.081	1.073	1.320 [†]	0.997	1.016		1.022	0.989	11.515
$h=36$	1.090	1.175	1.583 [†]	1.002	1.003		1.020	0.976	11.102
$h=48$	1.131	1.188	1.613 [†]	0.996	1.015		1.007	0.957	14.842
$h=60$	1.173 [†]	1.228	1.642 [†]	0.991	1.030 [†]		1.022	0.969	17.259

(*) See notes in Table 4. Source: Authors' elaboration.

4.2.4 Out-of-sample results: a summary

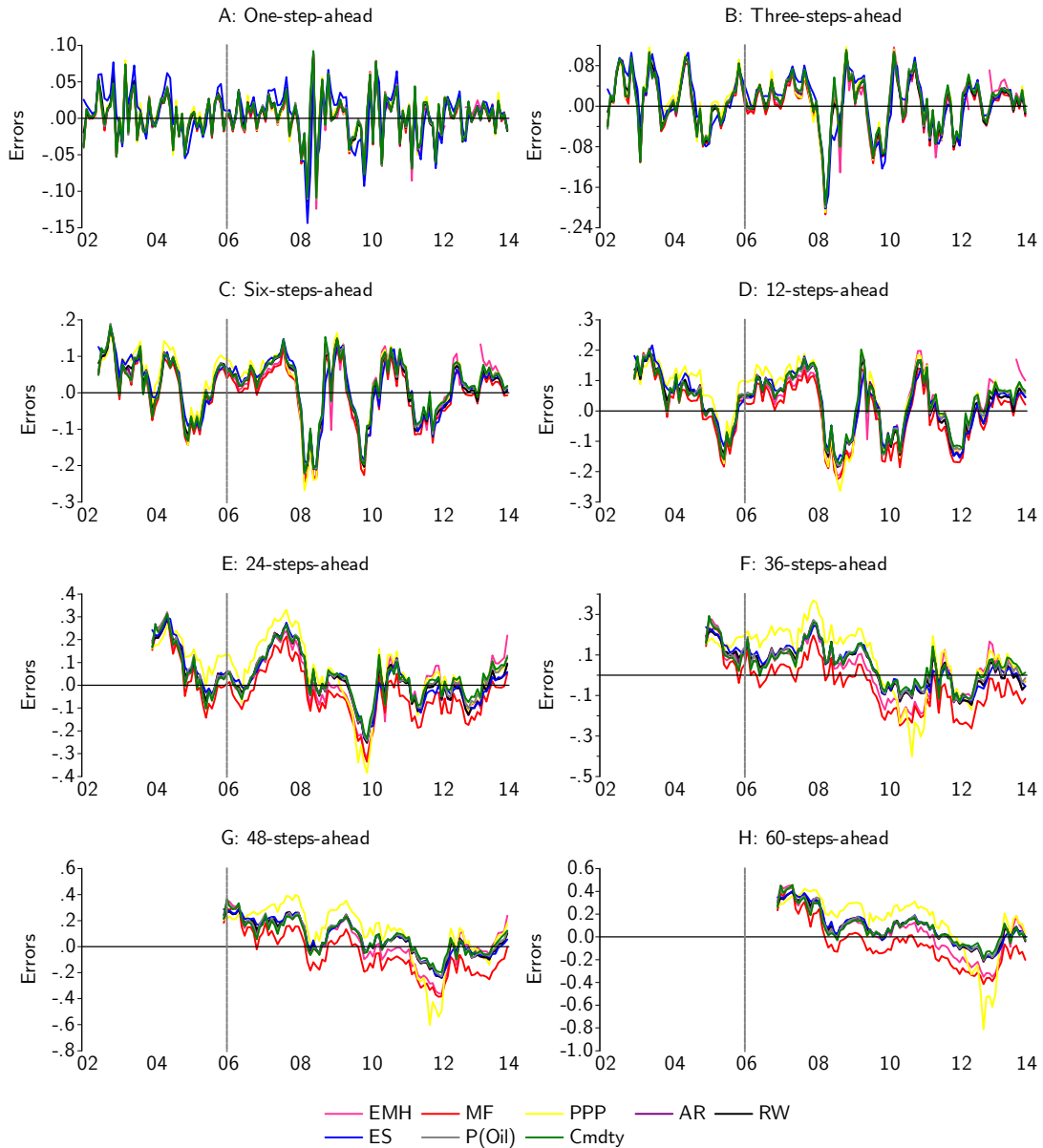
In Table 7 we present a summary of the models that exhibit the most accurate forecasts for a given country, horizon, and evaluation sample. We also show a ranking built using the number of times in which a model result as the best option independent of the country and horizon. Finally, we classify the best models into economics versus statistically founded.

For the UK, it is clear that with the shortened sample the MF is the best option, while with the extended sample are the statistical models. For Japan it is noticeable a EMH superiority with the shortened sample, and with the extended sample in the long run. Also, there is an important role for the Core model at the short-run. For the Euro Zone, the statistical models play an important role with the short sample, and in the short-run with the extended sample. Also with the latter sample, the Cmdty model results in the best option in the long-run.

Columns of Table 7 under heading "Models" remarkably summarise the main result of this article: first best FX forecasting models changes when considering a more volatile FX episode. In particular, the RW benchmark rarely outperforms any competing model until 2006.6, whereas it climbs to the first place when considering the full sample. In contrast, the MF model no longer outperforms the benchmark in

any case with the extended sample. In sum, when facing a more volatile period, the statistical models improve their performance following closer the performance exhibited by economics models.

Figure 6: Euro Zone. Forecasting Errors across Evaluation Sample (*)



(*) See notes in Figure 4. Source: Authors' evaluation.

5 Summary and concluding remarks

FX typically measures structural misalignments anticipating future short-run dynamics of key macroeconomic variables aiming to correct those misalignments with or without external intervention. The aim of this article is to analyse the out-of-sample behaviour of a bunch of statistical and economics-based models when forecasting FX for the UK, Japan, and the Euro Zone in relation to the US, emphasising the commodity prices boom of 2007-8 and the financial crisis of 2008-9.

Table 7: Summary of out-of-sample results (*)

	UK		Japan		Euro Zone		Models			Models	
	ES.I	ES.II	ES.I	ES.II	ES.I	ES.II	Model	ES.I	ES.II	ES.I	ES.II
$h=1$	MF	P(Oil)	EMH	RW	RW	RW	RW	2	7	Economics	
$h=3$	MF	AR	EMH	Core	RW	RW	Cmdty	–	5	17	14
$h=6$	MF	Cmdty	EMH	Core	MF	RW	EMH	6	5	Statistics	
$h=12$	MF	RW	P(Oil)	Core	AR	ES	Core	–	3	4	10
$h=24$	MF	RW	EMH	EMH	AR	Cmdty	ES	–	2		
$h=36$	MF	RW	EMH	EMH	MF	Cmdty	AR	2	1		
$h=48$	MF	ES	EMH	EMH	PPP	Cmdty	P(Oil)	1	1		
$h=60$	–	EMH	–	EMH	–	Cmdty	MF	9	–		
During crisis	PPP		MF		Cmdty		PPP	1	–		

(*) Source: Authors' elaboration.

We rely on the GL analysis which comprises three economic plus two statistical models evaluated with both financial and statistical criteria. The GL FX dataset includes the UK and Japan in relation to the US. We propose and analyse several modelling extensions to the GL article beyond just a sample increment. In particular, we include the Euro Zone, a forecast horizon of 60-steps-ahead, and three economic plus one statistical modelling extension in the analysis. Our modelling extensions are made through one of the three economic models of GL, the PPP, which is analysed along with the EMH and MF models. As the PPP model stands for domestic/foreign prices gap, we include a version based in core inflation. Also, we use the Brent price of oil and IMF's *Commodity Price Index* as a global price measures. We evaluate the models statistically regardless of the financial evaluation proposed in GL. The sample extension covers from 2006.6 until 2014.6; a period characterised of high volatility and breaks. Hence, it is expected for forecasting accuracy to suffer changes and to that end we also analyse the forecasting errors across the time.

Our results indicate that there are indeed changes of the first best models when considering the longer sample span. For the three countries—the UK, Japan, and the Euro Zone—none of the models that outperform in the GL sample remain as the best after the two aforementioned disruptions.

The results are mixed between statistical and economic models. Our results for the UK case indicate that the MF and AR outperform considering the GL sample span. When considering the whole evaluation sample, again the AR and now the P(Oil) model exhibit the best performance in the short run. Then, all the models exhibit similar accuracy with ES and EMH being the best alternatives at 60-steps-ahead. During the period of higher volatility, the PPP model predicts better the FX dynamics. For the case of Japan, the EMH model is the best alternative previous to 2007. When including the last part of the sample, the Core model as well as the remaining economic models shows the higher accuracy. The best model with higher FX volatility results is the EMH. Finally, for the Euro Zone there are two models outperforming in the first evaluation sample, MF and AR. When considering the whole sample, the Cmdty model outperforms the RW benchmark at six-steps-ahead onwards. The PPP and P(Oil) models exhibit promising results when predicting at long-run. As in the previous case, the best model when FX volatility is high is the EMH.

In sum, first best FX forecasting models changes when considering a more volatile FX episode. When facing a more volatile period, the statistical models improve their performance following closer the performance exhibited by economics models.

These results are important since they reveal the accuracy and confidence magnitudes when forecasting an important variable for policymaking as the FX is. Also, they provide robustness and insights for a

closer replication and extensions. This would be the case for the financial evaluation proposed in GL, suggested for further research.

References

1. Abhyankar, A., L. Sarno, and G. Valente (2005). "Exchange Rates and Fundamentals: Evidence on the Economic Value of Predictability." *Journal of International Economics* **66**(2): 325-348.
2. Andreou, A.S., E.F. Georgpoulos, and S.D. Likothanassis (2002). "Exchange-Rates Forecasting: A Hybrid Algorithm Based on Genetically Optimized Adaptive Neural Networks." *Computational Economics* **20**(3): 191-210.
3. Barberis, N. (2000). "Investing for the Long Run When Returns are Predictable." *Journal of Finance* **LV**(1): 225-264.
4. Berkowitz, J. and L. Giorgianni (2001). "Long-Horizon Exchange Rate Predictability?" *Review of Economics and Statistics* **83**(1): 81-91.
5. Blanchard, O.J. and S. Fischer (1989). *Lectures on Macroeconomics*. MIT Press, USA.
6. Boothe, P. and D. Glassman (1987). "Comparing Exchange Rate Forecasting Models: Accuracy versus Profitability." *International Journal of Forecasting* **3**(1): 65-79.
7. Brzezczynski, J. and M. Melvin (2006). "Explaining Trading Volume in the Euro." *International Journal of Finance and Economics* **11**(1): 25-34.
8. Cheung, Y.-W. and M.D. Chinn (1998). "Integration, Cointegration, and the Forecast Consistency of Structural Exchange Rate Models." *Journal of International Money and Finance* **17**: 813-830.
9. Cheung, Y.-W., M.D. Chinn, and A. García Pascual (2005). "An Economic Evaluation of Empirical Exchange Rate Models." *Review of Financial Studies* **22**(7): 3491-3530.
10. Cheung, Y.-W. and U.G. Erlandsson (2005). "Exchange Rates and Markov Switching Dynamics." *Journal of Business and Economics Statistics* **23**(July): 314-320.
11. Chinn, M.D. and R.A. Meese (1995). "Banking on Currency Forecasts: How Predictable is Change in Money?" *Journal of International Economics* **38**(1-2): 161-178.
12. Clarida, R.H. and M.P. Taylor (1997). "The Term Structure of Forward Premiums and the Forecastability of Spot Exchange Rates." *Review of Economics and Statistics* **89**: 353-361.
13. Clarida, R.L., L. Sarno, M.P. Taylor, and G. Valente (2003). "The Out of Sample Success of Term Structure Models as Exchange Rate Predictors: A Step Beyond." *Journal of International Economics* **60**(1): 61-83.
14. Dal Bianco, M., M. Camacho, and G. Pérez-Quirós (2012). "Short-Run Forecasting of the Euro-Dollar Exchange Rate with Economic Fundamentals." Documento de Trabajo 1203, Banco de España.
15. Della Corte, P., L. Sarno, and I. Tsiakas (2009). "An Economic Evaluation of Empirical Exchange Rate Models." *Review of Financial Studies* **22**: 3491-3530.

16. Dornbusch, R. (1976). "Expectations and Exchange Rate Dynamics." *Journal of Political Economy* **84**(6): 1161-1176.
17. Dornbusch, R., S. Fischer, and R. Startz (2010). *Macroeconomics*. Eleventh Edition. McGraw-Hill/Irwin, USA.
18. Engel, C. and J. Hamilton (1990). "Long Swings in the Exchange Rate: Are They in the Data and Do Markets Know It?" *American Economic Review* **80**(4): 689-713.
19. Engel, C., N.C. Mark, and K.D. West (2007). *Exchange Rate Models are Not as Bad as You Think*. *NBER Macroeconomics Annual*: 381-441.
20. Estrella, A. and F.S. Mishkin (1996). "The Yield Curve as a Predictor of US Recessions." *Current Issues in Economics and Finance* **2**(7).
21. Evans, M.D.D. (2011). *Exchange Rate Dynamics*. Princeton University Press, Princeton, USA.
22. Faust, J., J.H. Rogers, and J.H. Wright (2003). "Exchange Rate Forecasting: The Errors We've Really Made." *Journal of International Economics* **60**(1): 35-59.
23. Fat, C.M. and E. Deszi (2011). "Exchange-Rates Forecasting: Exponential Smoothing Techniques and ARIMA Models." *Annals of Faculty of Economics - Babes-Bolyai University* **1**(1): 499-508.
24. Frenkel, J. (1976). "A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence." *Scandinavian Journal of Economics* **78**: 200-224.
25. Frenkel, J. (1979). "On the Mark: A Theory of Floating Exchange Rates Based on Real Interest Differentials." *American Economic Review* **69**(4): 610-622.
26. Garratt, A., K.C. Lee, M.H. Pesaran, and Y. Shin (2006). *Global and National Macroeconometric Modelling: A Long-Run Structural Approach*. Oxford University Press, Oxford, UK.
27. Garratt, T. and K.C. Lee (2010). "Investing under Model Uncertainty: Decision based Evaluation of Exchange Rate Forecasts in the US, UK and Japan." *Journal of International Money and Finance* **29**(3): 403-422.
28. Giacomini, R. and H. White (2006). "Tests of Conditional Predictive Ability." *Econometrica* **74**(6): 1545-1578.
29. Goodfriend, M. (2008). "The Case for Price Stability with a Flexible Exchange Rate in the New Neoclassical Synthesis." *Cato Journal* **28**(2): 247-254.
30. Granger, C.W.J. and M.H. Pesaran (2000). "Economic and Statistical Measures of Forecast Accuracy." *Journal of Forecasting* **19**: 537-560.
31. Hakkio, C.S. (2009). "Global Inflation Dynamics." Working Paper 09-01, Federal Reserve Bank of Kansas City.
32. Hansen, P.R. (2009). "In-Sample Fit and Out-of-Sample Fit: Their Joint Distribution and its Implications for Model Selection." Preliminary Version of 19 June, 2009. Department of Economics, Stanford University, USA.
33. Hooper, P. and J. Morton (1982). "Fluctuation in the Dollar: A Model of Nominal and Real Exchange Rate Determination." *Journal of International Money and Finance* **1**: 39-56.

34. Hyndman, R.J., A.B. Koehler, J.K. Ord, and R.D. Snyder (2008). *Forecasting with Exponential Smoothing. The State Space Approach*. Springer Series in Statistics, USA.
35. Kandel, S. and R.F. Stanbaugh (1996). "On the Predictability of Stock Returns: An Asset-Allocation Perspective." *Journal of Finance* **LI**(2): 385-424.
36. Kilian, L. and M.P. Taylor (2003). "Why is it so Difficult to Beat a Random Walk Forecast of Exchange Rates?" *Journal of International Economics* **60**(1): 85-107.
37. Kim, B.J.C. and S. Mo (1995). "Cointegration and the Long-Run Forecast of Exchange-Rates." *Economics Letters* **48**(3-4): 353-359.
38. Kirikos, D.G. (2013). "How Did the Financial Crisis Affect the Forecasting Performance of Time Series Exchange Rate Models? Evidence from Euro Rates," *International Journal of Economics and Finance* **5**(2): 28-34.
39. Leitch, G. and J.E. Tanner (1991). "Economic Forecasts Evaluation: Profits versus Conventional Measures." *American Economic Review* **81**(3): 580-590.
40. MacDonald, R. and M.P. Taylor (1994). "The Monetary Model of the Exchange Rate: Long-Run Relationships, Short-Run Dynamics and How to Beat a Random Walk." *Journal of International Money and Finance* **13**(3): 276-290.
41. MacKinnon, J.G. (1996). "Numerical Distribution Functions for Unit Root and Cointegration Tests." *Journal of Applied Econometrics* **11**(6): 601-618.
42. Mark, N.C. (1995). "Exchange Rate and Fundamentals: Evidence on Long-Horizon Predictability." *American Economic Review* **85**(1): 201-218.
43. Mark, N.C. and D. Sul (2001). "Nominal Exchange Rates and Monetary Fundamental: Evidence from a Small Post-Bretton Woods Panel." *Journal of International Economics* **53**(1): 29-52.
44. Meese, R.A. and K. Rogoff (1983). "Empirical Exchange Rate Models of the Seventies: Do They Fit Out-of-Sample?" *Journal of International Economics* **14**: 3-24.
45. Meese, R.A. and A.K. Rose (1991). "An Empirical Assessment of Non-Linearities in Models of Exchange Rate Determination." *Review of Economic Studies* **58**: 603-619.
46. Melvin, M. and M.P. Taylor (2009). "The Crisis in the Foreign Exchange Market." *Journal of International Money and Finance* **28**(8): 1317-1330.
47. Melvin, M., J. Prins, and D. Shand (2013). *Forecasting Exchange Rates: An Investor Perspective*. In G. Elliot and A. Timmermann (2013). *Handbook of Economic Forecasting. Volume 2B*. Elsevier, North-Holland.
48. Møller, S.V. (2014). "GDP Growth and the Yield Curvature." *Finance Research Letters* **11**(1): 1-7.
49. Molodtsova, T. and D. Papell (2009). "Out-of-Sample Exchange Rate Predictability with Taylor Rule Fundamentals." *Journal of International Economics* **77**(2): 167-180.
50. Mussa, M. (1976). "The Exchange Rate, the Balance of Payments, and the Monetary and Fiscal Policy under a Regime of Controlled Floating." *Scandinavian Journal of Economics* **78**: 229-248.

51. Newey, W.K. and K.D. West (1987). "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* **55**(3): 703-708.
52. Owen, D. (2001). "Importance of Productivity Trends for the Euro. *European Economics for Investors*." Desdner Kleinwort Wasserstein.
53. Pesaran, M.H. and A. Timmermann (1995). "Predictability of Stock Returns: Robustness and Economic Significance." *Journal of Finance* **L**(4): 1201-1228.
54. Rosemberg, M. (2000). "The Euro's Long-Term Struggle." *FX Research Special Report Series 2*. Deustche Bank, London.
55. Sarno, L. and M.P. Taylor (2002). *The Economics of Exchange Rates*. Cambridge University Press, Cambridge, UK.
56. Satchell, S. and A. Timmermann (1995). "An Assessment of the Economic Value of Non-Linear Foreign Exchange Rate Forecasts." *Journal of Forecasting* **14**(6): 477-497.
57. Taylor, M.P. (1995). "The Economics of Exchange Rates." *Journal of Economic Literature* **33**(1): 13-47.
58. Taylor, M.P. (1989). "Covered Interest Arbitrage and Market Turbulence." *Economic Journal* **99**(396): 376-391.
59. West, K.D., H.J. Edison, and D. Cho (1993). "A Utility-Based Comparison of Some Models of Exchange Rate Volatility." *Journal of International Economics* **35**: 23-45.
60. Williamson, J. (2009). "Exchange Rate Economics." *Open Economies Review* **20**(1): 123-146.

A Data description and sources

In this Annex it is described the dataset in terms of its sources for further replication/checking purposes.

Table A1: Variable Description (*)

Variable	Country	Unity	Scale	Descriptor	IFS Code
<i>Foreign exchange rate</i>	UK	Nat. curr. per USD	None	Market rate, eop	112..AG.ZF...
	JPN	Nat. curr. per USD	None	Market rate	158..AE.ZF...
	EZ	Nat. curr. per USD	None	Market rate, eop	163..AE.ZF...
<i>Interest rates</i>	US	Percent per annum	None	Treasury Bill Rate	11160C..ZF...
	UK	Percent per annum	None	Treasury Bill Rate	11260C..ZF...
	JPN	Percent per annum	None	Discount rate, eop	15860.A.ZF...
	EZ	Percent per annum	None	Interbank rate (3 mths.)	16360B..ZF...
<i>Industrial production</i>	US	Index number	2010=100	Industrial prod. sa	11166..CZF...
	UK	Index number	2010=100	Industrial prod. sa	11266..CZF...
	JPN	Index number	2010=100	Industrial prod. sa	15866..CZF...
	EZ	Index number	2010=100	Industrial prod. sa	16366..CZF...
<i>Consumer price index</i>	US	Index number	2010=100	CPI all items city ave.	11164...ZF...
	UK	Index number	2010=100	CPI: all items	11264...ZF...
	JPN	Index number	2010=100	CPI: all JPN-588 items	15864...ZF...
	EZ	Index number	2010=100	Consumer prices	16364H..ZF...
<i>Money (M1)</i>	US	USD	Billions	M1 sa	11159MACZF...
	UK	Index number	2010=100	Narrow money, sa	<i>OECD</i>
	JPN	National currency	Trillions	M1, sa	15859MACZF...
	EZ	Billions	Blls. EUR	M1	16359MAUZF...
<i>Core inflation</i>	US	Index number	2010=100	CPI non food and engy.	<i>OECD</i>
	UK	Index number	2010=100	CPI non food and engy.	<i>OECD</i>
	JPN	Index number	2010=100	CPI non food and engy.	<i>OECD</i>
<i>Miscellaneous</i>		Index number	None	UK Brent oil price	11276AADZF...
		Index number	None	All commodities index	00176ACDZF...

(*) "eop" stands for end-of-period. "sa" stands for seasonally adjusted. Source: Authors' elaboration.

B Descriptive statistics: different samples

Table A2: Descriptive Statistics of Foreign Exchange Rates (*)

	Mean	Median	St. dev.	Min.	Max.	ADF-Stat.	<i>p</i> -value
<i>Full Sample: 1981.1–2014.6</i>							
UK							
Log-level	-0.490	-0.476	0.110	-0.871	-0.086	-1.250	0.195
$\Delta\log$	0.085	0.000	2.965	-12.893	12.554	-21.024	0.000
Japan							
Log-level	-4.839	-4.779	0.310	-5.625	-4.335	-1.806	0.068
$\Delta\log$	0.173	-0.131	3.162	-11.392	15.009	-21.201	0.000
Euro Zone							
Log-level	0.190	0.242	0.162	-0.172	0.458	-0.648	0.435
$\Delta\log$	0.098	0.028	3.013	-11.439	8.938	-13.171	0.000
<i>Evaluation Sample I: 2002.6–2006.6</i>							
UK							
Log-level	-0.551	-0.571	0.067	-0.658	-0.432		
$\Delta\log$	-0.447	-0.557	2.471	-5.540	4.827		
Japan							
Log-level	-4.728	-4.721	0.051	-4.808	-4.636		
$\Delta\log$	0.161	0.123	2.293	-5.540	5.127		
Euro Zone							
Log-level	0.164	0.186	0.087	-0.022	0.309		
$\Delta\log$	0.619	0.274	2.713	-4.952	6.424		
<i>Evaluation Sample II: 2006.7–2014.6</i>							
UK							
Log-level	-0.519	-0.482	0.105	-0.728	-0.351		
$\Delta\log$	0.077	0.000	2.650	-9.038	10.536		
Japan							
Log-level	-4.555	-4.561	0.140	-4.814	-4.335		
$\Delta\log$	0.132	0.426	2.806	-8.501	6.937		
Euro Zone							
Log-level	0.310	0.301	0.059	0.205	0.458		
$\Delta\log$	0.075	0.405	3.224	-11.439	8.938		

(*) ADF-test assuming a constant in the cointegrating equation. Lag-length criteria: BIC. Source: Authors' elaboration using data from IFS and OECD.

<p>Documentos de Trabajo Banco Central de Chile</p> <p>NÚMEROS ANTERIORES</p> <p>La serie de Documentos de Trabajo en versión PDF puede obtenerse gratis en la dirección electrónica:</p> <p>www.bcentral.cl/esp/estpub/estudios/dtbc.</p> <p>Existe la posibilidad de solicitar una copia impresa con un costo de Ch\$500 si es dentro de Chile y US\$12 si es fuera de Chile. Las solicitudes se pueden hacer por fax: +56 2 26702231 o a través del correo electrónico: bcch@bcentral.cl.</p>	<p>Working Papers Central Bank of Chile</p> <p>PAST ISSUES</p> <p>Working Papers in PDF format can be downloaded free of charge from:</p> <p>www.bcentral.cl/eng/stdpub/studies/workingpaper.</p> <p>Printed versions can be ordered individually for US\$12 per copy (for order inside Chile the charge is Ch\$500.) Orders can be placed by fax: +56 2 26702231 or by email: bcch@bcentral.cl.</p>
---	--

DTBC – 783

Desigualdad, Inflación, Ciclos y Crisis en Chile

Pablo García y Camilo Pérez

DTBC – 782

Sentiment Shocks as Drivers of Business Cycles

Agustín Arias

DTBC – 781

Precios de Arriendo y Salarios en Chile

Paulo Cox y Víctor Pérez

DTBC – 780

Pass-Through, Expectations, and Risks. What Affects Chilean Banks' Interest Rates?

Michael Pedersen

DTBC – 779

Fiscal Policy, Sectoral Allocation, and the Skill Premium: Explaining the Decline in Latin America's Income Inequality

Juan Guerra-Salas

DTBC – 778

Calvo Wages vs. Search Frictions: A Horse Race in a DSGE Model of a Small Open Economy

Markus Kirchner y Rodrigo Tranamil

DTBC – 777

Commodity Prices, Growth and Productivity: A Sectoral View

Claudia De la Huerta y Javier García-Cicco

DTBC – 776

Use of Medical Services in Chile: How Sensitive are The Results to Different Econometric Specifications?

Alejandra Chovar, Felipe Vásquez y Guillermo Paraje

DTBC – 775

Traspaso de Tipo de Cambio a Precios en Chile: El Rol de los Insumos Importados y del Margen de Distribución

Andrés Sansone

DTBC – 774

Calibrating the Dynamic Nelson-Siegel Model: A Practitioner Approach

Francisco Ibáñez

DTBC – 773

Terms of Trade Shocks and Investment in Commodity-Exporting Economies

Jorge Fornero, Markus Kirchner y Andrés Yany

DTBC – 772

Explaining the Cyclical Volatility of Consumer Debt Risk

Carlos Madeira

DTBC – 771

Channels of US Monetary Policy Spillovers into International Bond Markets

Elías Albagli, Luis Ceballos, Sebastián Claro y Damián Romero

DTBC – 770

Fuelling Future Prices: Oil Price and Global Inflation

Carlos Medel

DTBC – 769

Inflation Dynamics and the Hybrid Neo Keynesian Phillips Curve: The Case of Chile

Carlos Medel



BANCO CENTRAL
DE CHILE

DOCUMENTOS DE TRABAJO • Mayo 2016