Three Essays on the Predictive Content and Predictability of the Nominal Exchange Rates in a Changing World

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Declaration

I hereby declare that this thesis has been composed solely by myself and that it has not been submitted, in whole or in part, for any other degree.

Panteleimon Promponas

Signature: …………………….

To my family

and my beloved Eleni

Acknowledgments

I would like to express my deep and sincere gratitude to my supervisors, Prof David Peel and Prof Mike Tsionas, for their excellent guidance and support throughout this journey. Also, I would like to thank Dr Efthymios Pavlidis for his constructive comments and encouragement.

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I will never forget their contribution and help.

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Abstract

This thesis examines the predictive power and the predictability of the nominal USD/GBP exchange rate changes in a world with structural instabilities. In Chapter 2 we mainly focus on the predictive content of the exchange rates in an attempt to forecast the Taylor rule fundamentals, such as the output gap, the inflation rate and the real exchange rate of the U.S. and the U.K. We employ time-varying econometric techniques, taking into account possible non-linearities and time-variations of the Taylor rule relationships, while we also use Bayesian methods and real-time (vintage) data for the variables that suffer from consecutive revisions. Chapter 3 reviews the well-known 'Meese and Rogoff' puzzle which describes the inability of the macroeconomic fundamentals to forecast the exchange rate returns. Starting with a critical survey of the exchange rate forecasting literature, we move on to testing a wide range of traditional and empirical macro fundamentals-based models using various linear and non-linear models, as well as a DSGE model. We examine whether making provisions for the instability and predictive relevance of the fundamental, the out-of-sample performance of our models is improved or not. Finally, Chapter 4 is motivated by the disaster risk literature, examining the in-sample and out-of-sample predictive impact of the foreign policy crises of the U.S. and the U.K. on the USD/GBP exchange rate returns. Using the foreign policy crisis as an approximation for the time-varying disaster risk of these two economies, we study how exchange rate returns are affected by crises of different severity and violence, once combined with other macroeconomic predictors.

Chapter 1

Introduction

In the world of today, currency is one of the principal driving forces of a national economy and is exchanged for trading purposes. People traveling around the world may need to hold foreign currency for personal transactions, while international firms and governments demand foreign currency for importing products or buying services from abroad. Hence, the exchange rate of two currencies plays a crucial role in consummating a transaction at an international level, as well as bridging the economic and financial relationship of different countries or parties around the world.

Given the importance of the foreign exchange rates, researchers are very keen to explore their behaviour, dynamics, predictive content and relationship with macroeconomic variables such as the GDP, the inflation rate, the interest rate and the money supply. Engel and West (2005) find that exchange rates Granger-cause the Taylor rule fundamentals, concluding that exchange rates are likely to be more useful in forecasting the fundamentals than the opposite. This scenario was examined using an in-sample framework, revised data and assuming structural stability of the Taylor rule relationships. In Chapter 2, we novelly extend this idea by investigating the out-of-sample predictive content of the exchange rates in forecasting the Taylor rule fundamentals (output gap, inflation and real exchange rate) of the U.S. and the U.K. We employ time-varying econometric techniques, taking into account the possible non-linearities and time-variations of the Taylor rule relationships, while we also use real-time (vintage) data for the variables that suffer from consecutive revisions. Finally, we employ Bayesian econometric methods, which have become increasingly interesting, to draw a priori more predictive power from the exchange rates than the rest predictors. The interest in this exercise is whether Engel and West's (2005) findings are robust under the different data structure, environment and methods that we examine.

One of the long-standing puzzles in international economics which describes the inability of the macroeconomic variables to predict the exchange rate movements, has become an 'arena' for many researchers and practitioners for the last three decades. The literature refers to it as the 'exchange-rate disconnect puzzle', or the 'Meese and Rogoff puzzle', due to the seminal and influential empirical works of Meese and Rogoff (1983a, 1983b). Apart from the 'disconnection' issue described in their research papers, they also pinpoint the fact that a 'naïve' a-theoretical random walk model is more capable of forecasting the exchange rate movements, than any other more complex and sophisticated economic model, especially at short horizons. Hence, this puzzle has led many researchers to develop several econometric techniques, theoretical and empirical models in an attempt to overturn these findings and generate better forecasts than the benchmark random walk model.

In Chapter 3, we revisit the aforementioned puzzle by conducting a real-time exchange rate (USD/GBP) forecasting race between theoretical and empirical models proposed by the existing literature and the driftless random walk model which seems to be the toughest benchmark model. We include a wide range of models based on traditional macroeconomic predictors as well as a structural DSGE model which describes and mimics the behaviour of the economies. We pay special attention to the time-variations and the unstable relations between the predictors of our models and the exchange rates by employing and comparing the forecasting performance of various homoscedastic and heteroscedastic TVP-Bayesian VAR models. In addition, a Dynamic Model Averaging and Selection developed by Raftery et al. (2010), is included in the race, allowing for a different set of predictors to hold at each time period, and hence, indicating which fundamentals are more relevant in forecasting the exchange rate returns and at which periods. This forecasting race is of particular interest to the reader, as it compares models with different specification, predictors and complexity level, with results indicating which model has the best out-of-sample performance and which predictors are more relevant.

Chapter 4 examines the relationship between the nominal USD/GBP exchange rate changes and the foreign policy crises of the last three decades, using both in-sample and out-of-sample frameworks. Motivated by the disaster risk literature and the empirical work of Barro (2006), Farhi and Gabaix (2016) and Berkman et al. (2011), we use the foreign policy crises of the U.S. and the U.K. as approximations for the time-varying disaster risk of these economies, and combining them with the macroeconomic fundamentals, we examine their in-sample and out-of-sample predictive impact on the exchange rate returns. In this analysis, we examine crises of various levels of severity and intensity, either triggered or received by the U.S. and the U.K., while we also categorise them into crises that start, terminate or being under way in each time period. The results of this chapter indicate the usefulness of the foreign policy crises as an additional predictor of the theoretical and empirical exchange rate models.

Finally, Chapter 5 summarises the main findings and conclusions of the thesis along with suggestions for future research.

Chapter 2

Forecasting the Taylor Rule Fundamentals in a Changing World: The Case of the U.S. and the U.K.

2.1 Introduction

Since the empirical work of Meese and Rogoff (1983a, 1983b), it has been well known that theoretical exchange rate models based on macroeconomic fundamentals cannot outperform the naïve random walk in out-of-sample accuracy. Forecasting exchange rate changes using the macroeconomic fundamentals as predictors has become an 'arena' and debate for many researchers who want to overturn this pessimistic finding. Engel and West (2005) introduce a key theorem explaining the random walk behaviour of the exchange rates and move to shift the terms of the debate by postulating the question of whether the exchange rates can predict the fundamentals. Using the Taylor rule of two countries, they derive a model within the asset-pricing framework, focusing on the in-sample predictability by conducting Granger-causality tests between the exchange rate changes and the fundamentals. They conclude that the exchange rate changes Granger-cause the macroeconomic fundamentals, such as the relative money supplies, outputs, inflation rates and interest rates, compared to the far weaker causality from the fundamentals to the exchange rates. This finding lead them to underline the fact that the exchange rate changes are likely to be useful in forecasting the future values of the fundamentals. They examine this scenario using the bilateral exchange rates of the U.S. dollar versus the currencies of Canada, France, Germany, Italy, Japan, and the United Kingdom, using revised data for the inflation and the output, while structural stability in the interest rate reaction functions is also assumed.[1]

This chapter is mainly motivated from the empirical work of Engel and West (2005) (hereafter EW05), though we take it a step further, building an out-of-sample

[1] The study of Engel and West (2005) is a remarkable one, testing the predictive content of the exchange rates using a present-value model, but it is not the only one. Chen et al. (2010) investigate the predictive ability of the nominal exchange rates to forecast the global commodity prices. They find that 'commodity currencies' (countries that depend heavily on primary commodity exports) can forecast the commodity prices both in-sample and out-of-sample, taking into account the time-varying environment.

forecasting exercise for the Taylor rule fundamentals (output gap, inflation, and real exchange rate) recognising the need of many institutions, central banks, governments, and practitioners for reliable forecasts of the major macroeconomic variables. We use the Taylor rule introduced by Taylor (1993), and after some modifications introduced by Engel and West (2006), Molotdsova and Papell (2009), and Clarida, Gali and Gertler (1998), we allow (by imposing the appropriate priors) for the exchange rate changes to forecast the fundamentals using a vector autoregressive (VAR) framework, where time-variation in the parameters of the Taylor rule relationships is allowed as well. Existing literature supports the view that interest rate reaction functions suffer from structural changes, non-linearities, asymmetric information and preferences or shifts of the monetary policy behaviour every time the chairmanship of a Central Bank changes (see, e.g. Surico, 2007; Castro, 2011; Nelson, 2000; Dolado et al., 2004). Also, D'Agostino et al. (2013), Primiceri (2005), and Sarantis (2006) argue that economies in countries around the world have undergone many structural changes, and models should incorporate mechanisms in order to evolve over time and deliver better forecasts. Therefore, a Bayesian TVP-VAR model, allowing for both intercept and coefficients to change over time, will provide us with the forecasting equations we need for the Taylor rule fundamentals and also allow us to draw a priori more predictive power from the exchange rates than the rest of the predictors.

In this work, we employ vintage (or real-time) data compared to EW05 who use revised data for the output and inflation, since Orphanides (2001) shows that evaluating Taylor rules using ex post revised data leads to different policy reactions than estimating them with real-time data[2]. Therefore, he argues that analysis and evaluation of the monetary policy decisions must be based on information available in real time. Also, Croushore and Stark (2001), Stark and Croushore (2002), and Croushore (2011) present the benefits and forecasting gains that a researcher may have by employing a real-time dataset (such as that developed in the Federal Reserve Bank of Philadelphia with the cooperation of the University of Richmond).[3] All of the aforementioned studies argue

[2] According to Croushore (2006), 'vintage' refers to the date at which the data become publicly available. From now on, we call 'vintage data' the available observations as announced on a specific date and the collection of those vintages 'real-time dataset'. A detailed description of the triangular structure of a real-time dataset can be found in Croushore and Stark (2001).
[3] The following link leads to real-time datasets for the major macro variables of the U.S.: www.philadelphiafed.org/research-and-data/realtime-center/real-time-data/. Similar datasets for the variables of the U.K. can be found on the website of the Bank of England.

that results from forecasting exercises may be misleading when revised data are used rather than data that were available to the agents at the time they were generating the forecasts. It is striking that Croushore (2011) concludes with the remark that there is no excuse for someone who wants to conduct a forecasting exercise or a policy analysis not to employ real-time data as, nowadays, they are easily accessible and widely known.[4] Hence, we carry out a real-time forecasting exercise using vintage data rather than an out-of-sample exercise with fully revised data.

A multiple equation vehicle based on real-time information will help us measure how these unstable policy rules affect the rest of the economy by generating 1-, 2-, 3- and 4-quarters-ahead iterated forecasts for the Taylor rule fundamentals using both recursive and rolling regressions. We consider the U.S. as the home country and the U.K. as the foreign country. We also include, for comparison purposes, a BVAR and a classical VAR model in the forecasting exercise, while the forecasting performance of the models is compared with that of the driftless random walk model using the relative root mean squared forecast error (RMSFE) and the relative mean absolute forecast error (MAFE) ratios. Clark and West's (2006, 2007) test of predictive superiority is also used for the significance of the out-of-sample results.

Our main findings show that the TVP-BVAR model, which draws a priori more predictive content from the exchange rates, is able to generate good forecasts for the U.S. output gap, the U.K output gap at longer horizons, the U.K. real exchange rate at the short horizon, and the U.K. inflation under the rolling scheme only. To the best of our knowledge, there is no previous study extending EW05's work in these directions.

The remainder of this chapter is structured as follows. In section 2, we examine the monetary policy of the U.S. and the U.K., with evidence from the literature and our own empirical findings about their structural changes and instabilities. Section 3 elaborates on the specification and the estimation methodology of our TVP-BVAR model, while, in section 4, the real-time data, forecast implementation, and evaluation are discussed. Section 5 summarises the empirical results, and section 6 provides the conclusions.

[4] Nevertheless, we must mention and encourage the national statistical offices around the world to try harder in collecting data from historic manuscripts and archives, since for some variables, vintages do not go as far back as researchers would like, while for other countries (mostly developing) this kind of data are not even available.

2.2 Monetary policy and structural breaks of U.S. and U.K.

In an attempt to describe the U.S. monetary policy reaction function in an environment in which the debate between discretionary and algebraic-rule policies was taut, and admitting the difficulty in formulating an appropriate algebraic formula that monitors the macroeconomic figures, John Taylor introduced in 1993 an interest rate reaction function known as the 'Taylor rule'. Hence, according to Taylor (1993), there should be a balance between discretion and policy rules in the sense that, together, the critical thinking, reasoning, and technical formulas should be the optimal tool for the policymaker. He argues that monetary authority in the U.S. changes the short-term nominal interest rates (Federal fund rates) in response to the deviations in the inflation rate from its target level and real output from its potential level. The reaction function can be written as:

$$i_t^* = \alpha(\pi_t - \pi^*) + \beta y_t^{gap} + \pi_t + r'', \tag{2.1}$$

where i_t^* is the target for the short-term nominal interest rate, π_t is the inflation rate, π_t^* is the target rate of inflation, y_t^{gap} is the output gap (deviation of actual real GDP from its estimated potential level), and r'' is the equilibrium real interest rate. Taylor (1993) advocates that the representative Fed policy function might set $\alpha = \beta = 0.5$, an inflation target of 2%, and an equilibrium real interest rate of 2% as well. Hence, the interest rate should respond with fixed positive weights to the inflation and output gap.[5] The above equation can be written as:

$$i_t^* = \delta + \beta y_t^{gap} + \kappa\pi_t, \tag{2.2}$$

where $\delta = r'' - a\pi^*$ and $\kappa = 1 + a$. When $\kappa > 1$ (positive deviation of inflation from its target level), the literature refers to it as the *Taylor-principle* and the short-term nominal interest rate should be increased more than 1:1 with inflation, achieving an increase in the real interest rate.

[5] It is assumed that there is no distinction between the target and the actual short-term nominal interest rate since it is achieved within the period. Also, central banks may take into account all available information such as expectations of the inflation or the level of output. Hence, Clarida et al. (1998) introduce the *forward-looking* version of the Taylor rule where expectation of the rate of inflation is introduced for period $t+n$, given the information set Ω available to the monetary authorities up to time t.

Clarida et al. (1998) and Woodford (2003) consider the possibility that central banks smoothly adjust their short-term nominal interest rate as:

$$i_t = (1-\rho)i_t^* + \rho i_{t-1} + u_t\,, \tag{2.3}$$

where $\rho \in [0,1]$ captures the smoothing rate of the adjustment and u_t is assumed to be an *i.i.d.* process. With regard to the standard backward-looking version of the Taylor rule, which is considered in this chapter, one can derive the estimable equation, combining equations (2.2) and (2.3):

$$i_t = \lambda + \alpha_\pi \pi_t + \beta_y y_t^{gap} + \rho i_{t-1} + \varepsilon_t\,, \tag{2.4}$$

where $\alpha_\pi = (1-\rho)\kappa$, $\beta_y = (1-\rho)\beta$ and $\lambda = (1-\rho)\delta$.

The monetary policy rule can also be derived from the solution of an intertemporal optimisation problem in which the central bank minimises a symmetric quadratic loss function with a linear aggregate supply function (Surico, 2007). Castro (2011) mentions that symmetry of the loss function is not the case in the real world. Different weights of positive and negative inflation and output gap may be assigned by the monetary authorities, leading to asymmetric preferences, and therefore, to a non-linear Taylor rule (see, e.g. Nobay and Peel, 2003). Also, in an attempt to interpret Blinder's (1998) words (when Blinder was describing his experience as Vice Chairman of the Fed), Surico (2007) pinpoints the fact that political pressure may cause the central bank to intervene asymmetrically.

Dolado et al. (2004) construct a model that considers both asymmetries in the preferences of the central bank and non-linearities of the Phillips curve, where the aggregate supply curve is a convex function of the output gap. They also consider the case in which the non-linear Taylor rule gives rise to the sign and size asymmetries. *Sign* asymmetry appears when the response to an increase in inflation is larger than the response to a decrease, although they may have the same magnitude. What they call *size* asymmetry is the non-linear relation between the change in the interest rate and the change in the inflation rate. They focus on the periods 1970:M1–1979:M6 and 1983:M1 –2000:M12, which correspond to the chairmanships of the central bankers Arthur Burns–William Miller and Paul Volcker–Alan Greenspan, respectively. Their empirical results indicate that, prior to 1979, the Fed's policy could be well described by a linear Taylor rule, and the central bank preferences becoming quadratic in inflation, while after 1983 U.S. interest rate reaction function seems to be described more accurately from a non-linear Taylor rule since it responds more aggressively to the inflation volatility than to the level. They conclude that, during the Volcker–Greenspan period, asymmetric central bank preferences for the inflation appeared with positive deviations of the inflation from the target, which are weighted more than the negative ones.

A slightly different model is that of Surico (2007), who derives the analytical solution of the central bank's problem, whereby, at the same time, the monetary transmission mechanism is New-Keynesian and asymmetric preferences in both inflation and output gap are allowed. He finds that U.S. monetary policy followed a non-linear Taylor rule during the pre-Volcker period, with the asymmetry being detected in the fact that the Fed assigned less weight to output expansion than output contraction of the same magnitude. However, results for the period after 1982 strongly suggest the symmetric preferences of the central bank. Furthermore, of great importance are the public speeches and interviews of 'strong' people who worked for the Fed and U.S. government. Surico (2007) cites a conversation (quoted from Nelson, 2005) between U.S. President Nixon and Arthur Burns (Chairman of the Fed) and some lines from Nixon's interview in the *Kansas City Star* in 1970 (quoted from De Long, 1997).

Nixon argues in the newspaper interview in the *Kansas City Star* that: '*[the consensus for Mr. Burns at his swearing-in] is a standing vote of approval, in advance, for lower interest rates. […] I have very strong views, and I expect to present them to Mr. Burns. I respect his independence, but I hope he independently will conclude that my views are the right ones.*'

Conversation between Nixon and Burns: '*I know there's the myth of the autonomous Fed... [short laugh] and when you go up for confirmation some Senator may ask you about your friendship with the President. Appearances are going to be important, so you can call Ehrlichman* (Assistant to President Nixon for Domestic Affairs) *to get messages to me, and he'll call you.*'

So, we have some signs that there were interventions and political pressure on the central bankers for asymmetric preferences (e.g. lowering the interest rates or increasing money growth) and hence probably gaining greater reputation and numbers of voters, at the end of the day.

A different perspective in testing and estimating the monetary policy rule is conducted by Castro (2011), using a logistic smooth transition regression (LSTR) model, which allows for smooth endogenous regime (policy rule) switches, while an LM test is used to draw inferences as to whether the U.S. policy rule follows a linear or an LSTR model. Results show that, during the period 1982:M7–2007:M12, the Fed was targeting an average target of inflation of around 3.5%, while it can almost be characterized by a forward-looking linear Taylor rule since the linearity hypothesis of the forward-looking model is rejected only at 10% significance level against the LSTR model. Regarding the case of U.K., the non-linear STR model is estimated for the period 1992:M10–2007:M12, indicating that the Bank of England (BoE) reacted actively to inflation when the inflation rate was outside the target range of 1.8%–2.4%, whereas once inside it responded only to the output gap. On the other hand, Martin and Milas (2004) study the behaviour of monetary policy in the U.K. before and after 1992 using a forward-looking policy rule adopting an inflation targeting. They find that, in the post-1992 period, monetary authorities followed an asymmetric policy, trying to keep inflation between 1.4% and 2.6%, whereby central bank responded more aggressively when inflation was above this target and more passively to the negative inflation gaps.

A hyperbolic tangent smooth transition regression (HTSTR) model is used by Cukierman and Muscatelli (2008), who estimate the model after breaking down their sample into four periods: 1960:M1–1970:M1, 1970:M2–1979:M3, 1982:M4–1987:M3, and 1987:M4–2005M4, corresponding to the chairmanships of Martin, Burns–Miller, Volcker, and Greenspan, respectively, in the U.S. Fed. During Martin's period, authors suggest that Fed preferences were more averse to positive than to negative inflation gaps – what they call *inflation-avoidance preferences* (IAP). As for the Burns–Miller and Greenspan periods, although there is no evidence for non-linearity in inflation, the authors find the Fed being more averse to negative than to positive output gaps – what they call *recession-avoidance preferences* (RAP). The results for Volcker's period confirm the findings of Surico (2007) of no asymmetric preferences, giving a possible explanation that, during that period the Fed reacted to both inflation and recession avoidance in such a way that those asymmetries offset each other. As for the case of the

U.K., the results suggest that the 1979:M3–1990:M3 period is characterised by RAP, while the 1992:M4–2005:M4 period is characterised by IAP.

A three-regime threshold regression model, motivated by Orphanides and Wilcox (2002) and Taylor and Darvadakis (2006), is used in Lamarche and Koustas (2012) to capture possible asymmetries in the Fed's reactions. Covering the period 1982:M3–2003:M4 (the Volcker–Greenspan period) and using the expected inflation as threshold, they suggest that the Fed followed a non-linear reaction function, behaving completely differently in the two outer regimes. More specifically, when expected inflation lay within the middle–regime (2.8%–3.9%), it seems that the Fed behaved with policy inaction. However, when expected inflation exceeded the upper threshold, authorities reacted aggressively to cool down the economy, whereas, in the case in which expected inflation appeared below the lower threshold, the policy reaction was to decrease the real interest rates. On the other hand, Taylor and Darvadakis (2006) employ both two- and three-regime models to examine the behaviour of the reaction function of the U.K. for the period 1992:M10–2003:M1. They find that, when the inflation rate exceeded the threshold of 3.1%, a forward-looking Taylor rule was followed by the BoE, with more weight attached to the expected inflation deviations from the target than deviations of the output, however, when inflation was lower than 3.1%, a near random walk process with very small but significant responses to the output gap characterised the interest-rate-setting behaviour of the BoE.

Similar empirical findings are delivered by other studies on the behaviour of the interest rate reaction function of the BoE. After analytically examining the behaviour of the BoE from 1972:M6 to 1997:M5, when the BoE gained operational independence, Nelson (2000) underlines how important is for the researcher to allow for the parameters to evolve over time when estimating monetary policy rules. He breaks down the full sample into six regimes, estimating both the backward- and forward-looking versions of the Taylor rule. For the period 1972:M7–1976:M5, the BoE seemed to respond mainly to the lagged output gap than to inflation, whereas for the 1976:M6–1979:M4 period (pre-Conservative government period), 'tightness' of the monetary policy was a dominant characteristic. Regarding the period in which Thatcher's government was elected (1979:M5–1987:M2), interest rates seemed to respond more to current inflation rather than to expected inflation. The period in which GDP was linked to the deutsche mark and the BoE was following somewhat closely the monetary policy of the German central bank (1987:M3–1990:M9), short-term nominal interest rates responded more to the German rate rather than to the domestic variables of the U.K. economy.

2.2.1 Bai and Perron tests for multiple structural changes in the Taylor rule of the U.S. and the U.K.

It is worth examining the existence of structural changes in the interest rate reaction function for both the U.S. and the U.K. Then, we can support the view that time-varying parameters in the forecasting exercise, dealing with the structural breaks and instabilities, can be proved helpful for delivering more accurate forecasts for the fundamentals. Hence, we follow the popular method of Bai and Perron (1998, 2003) for testing multiple structural breaks. Details about the model specifications, estimation and test statistics for multiple breaks can be found in Appendix A.

Model and Data

To examine the presence of structural breaks in the Taylor rule relationship of the U.S. and the U.K., we employ the standard Taylor rule incorporating the interest rate smoothing adjustment. Hence, we recall the estimable equation (2.4):

$$i_t = \lambda + \alpha_\pi \pi_t + \beta_y y_t^{gap} + \rho i_{t-1} + \varepsilon_t ,$$

which we treat as a pure structural change model. Quarterly data for the period 1971:Q2–2012:Q3 are used for this analysis. Regarding the short-term nominal interest rate, the Effective Federal Fund Rate (target for the key interbank borrowing rate) is used as a proxy for the U.S. interest rate from the Federal Reserve Bank of St. Louis and the Official Bank Rate from the BoE for the U.K., which are divided by 100. Regarding the inflation rate, we use the GDP deflator (seasonally adjusted) and compute it as the rate of inflation over the four previous quarters, $\pi_t = deflator_t - deflator_{t-4}$ (GDP deflator in natural logs). The price index for GDP comes from the Federal Reserve Bank of Philadelphia for the U.S. and from the BoE for the U.K. The output gap is defined as the deviation of the actual real GDP from its potential estimated level. For this study, we use the most known and commonly used univariate method, which is the Hodrick and Prescott (1997) filter (HP). HP is widely used by international organisations and institutions such as the IMF and the European Central Bank which extracts from a time-series y_t the growth component, trend, T_t. The real GDP (seasonally adjusted) in natural logs is used as a proxy for the actual real output. For the U.S., data come from the Federal Reserve Bank of Philadelphia and for the U.K. from the Office of National Statistics (ONS). Before applying the filter we backcast and forecast our data by 12 data points with an AR(4) model in order to correct for the end-of-sample problem that filters such as the HP present (e.g. Clausen and Meier (2005)).

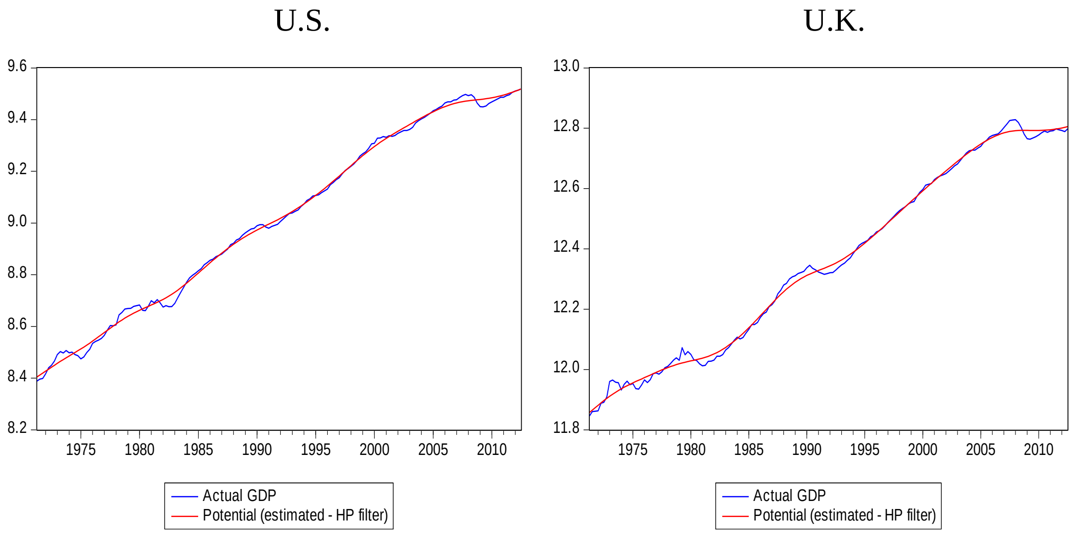

Figure 2.1: Actual and potential GDP (estimated with HP filter) of U.S. and U.K.

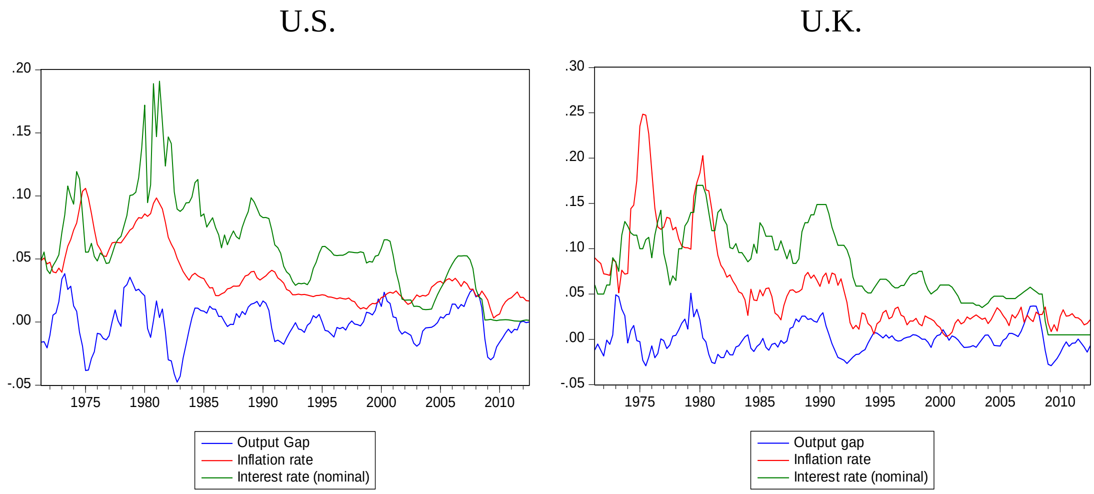

Figure 2.2: Inflation rate, short-term nominal interest rate, and output gap (HP filtered)

Results

We report results for the Double maximum (*UDmax* and *WDmax*) test and the *supF*(*k*) of 0 *vs k* number of breaks. The indicated change points are estimated using the global minimisation, where the maximum number of breaks is set to 8.

Table 2.1: Bai and Perron (1998) multiple breakpoint tests of the U.S. policy rule

Multiple breakpoint tests.
Bai-Perron (1998) tests of 1 to M globally determined breaks.
Sample: 1971Q2 - 2012Q3.

Significant F-statistic largest breaks:	8
UDmax determined breaks:	7
WDmax determined breaks:	8

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1	2.891715	11.56686	11.56686	16.76
2 *	21.45686	85.82744	97.72200	14.72
3 *	19.32798	77.31193	97.42465	13.30
4 *	15.40495	61.61978	84.30592	12.25
5 *	17.14363	68.57451	101.7988	11.29
6 *	20.72162	82.88650	133.3184	10.42
7 *	561.3443	2245.377	3928.238	9.58
8 *	544.0854	2176.342	4311.523	8.46

UDMax statistic*	2245.474	UDMax critical value**	17.00
WDMax statistic*	4311.078	WDMax critical value**	18.38

Estimated break dates: 8

1976:Q4, 1980:Q4, 1984:Q4, 1989:Q3, 1992:Q4, 1998:Q4, 2002:Q4, 2008:Q4

Notes: Included observations: 166. Break test options: trimming 0.10, max. breaks 8, sig. level 0.05. Test statistics employ HAC covariances (Pre-whitening with lags = 1, Quadratic-Spectral kernel, Andrews bandwidth). Allow heterogeneous error distributions across breaks.
* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

The estimated break of 1980:Q4 is not far from the date at which Volcker took over the Chairmanship of the Fed, and this period is also reported as a regime shift in the majority of the economic literature. Qin and Enders (2008) estimate the interest rate reaction function of the U.S. before and after Greenspan period and conclude that the Taylor rule specification that best fits the data differs, implying a change in the monetary policy. Our test captures this change, although it suggests that this took place one year later. Regarding the 1984:Q4 break, it is difficult to historically clarify the significance and importance of this date. Nevertheless, the 'Plaza Agreement' between the U.S. and other major economies, which led to the devaluation of the U.S. dollar, could be an event causing this break (Duffy and Engle-Warnick, 2006). The 1989:Q3 break estimated by the test is documented in Goodfriend (2002) as a period of rising inflation, with the Fed maintaining a neutral response and hesitation against this inflationary surge. Data also indicate an increase in wage inflation, a fall in the unemployment rate, and somewhat steady productivity growth around this period. The next structural break reported by the test is at the end of 1992. Goodfriend (2002) describes the 1990:Q3–1994:Q1 period as a war, recession, and disinflation period. The Gulf War, the significant increase in oil prices by 20 dollars per barrel, and the price drop due to the recession that the war brought were the main events affecting not only the U.S. economy in that period. During that period, there was a remarkable decrease in the federal funds rate from 6% to 3% by the end of 1992, an increase in the real output growth rate, and a ceaseless upward trend in the unemployment rate of around 8% by June 1992. This period is documented by Goodfriend (2002) as the 'jobless recovery'. In 1998:Q4, Bai and Perron (1998) (BP) test estimates the next structural break after the birth of the euro. As Goodfriend (2002) mentions, the period of 1996–1999, the U.S. economy presented a 'boom' in its productivity growth of 2.4% per year, on average, increasing household income and spending. These auspicious economic conditions were followed by a burst in technological advances and investment by firms in an attempt to modernise their assets, expand production even more, and hire a more educated and productive labour force in order to become more competitive.[6] The U.S. invasion of Iraq in March 2003, following the attack on the World Trade Centre on 11 September 2001, in which approximately 800,000 people lost their jobs causing an increase in government spending and a decline in consumer spending, could be the reason why the BP test estimates 2002:Q4 as a structural change in monetary policy. The last break is located in 2008:Q4, when the financial crisis and the credit crunch started in the U.S. housing sector and the Fed dropped interest rates close to the zero lower bound.

[6] Goodfriend (2002) reports two other events during that period: the financial crisis in East Asia and the debt default of the Russian Federation.

Regarding the U.K., we report the estimated structural break dates obtained from the BP test with the maximum number of breaks equal to five. Evidence is less clear for the number of breaks since *UDmax* suggests two breaks, while *WDmax* suggests four, and $supF_T(5)$ suggests five breaks.

Table 2.2: Bai and Perron (1998) multiple breakpoint tests of the U.K. policy rule

Multiple breakpoint tests.
Bai-Perron tests of 1 to M globally determined breaks.
Sample: 1971Q2 - 2012Q3.

Significant F-statistic largest breaks:	5
UDmax determined breaks:	2
WDmax determined breaks:	4

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1	2.317696	9.270784	9.270784	16.19
2 *	5.897055	23.58822	27.73372	13.77
3 *	5.244817	20.97927	27.90915	12.17
4 *	4.902727	19.61091	29.42545	10.79
5 *	4.136487	16.54595	29.46963	9.09

UDMax statistic	23.5882	UDMax critical value**	16.37
WDMax statistic*	29.4696	WDMax critical value**	17.83

Estimated break dates: 5

1978:Q2, 1987:Q1, 1993:Q4, 2000:Q2, 2007:Q1

Notes: Included observations: 166. Break test options: trimming 0.10, max. breaks 8, sig. level 0.05. Test statistics employ HAC covariances (Pre-whitening with lags = 1, Quadratic-Spectral kernel, Andrews bandwidth). Allow heterogeneous error distributions across breaks.
* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

The first estimated break that $supF_T(5)$ suggests is in 1978:Q2, when ten months previously, a new regime began with the election of Thatcher's Conservative government. The first quarter of 1987 is the next suggested break, when, the informal link between sterling and the deutsche mark occurred, along with the very close relationship between U.K. and German monetary policy. The third change is estimated in 1993:Q4, when, in the previous year, the government announced the new policy of inflation targeting; for this reason, this date is used by the majority of studies to test the regime shifts of U.K. monetary policy. The forth break is in 2000:Q2, when inflation dropped. The last break is in 2007:Q1, at the beginning of the credit crunch.

2.3 Motivation and TVP-BVAR forecasting model

Engel and West (2005) use an asset-pricing framework to explain the random walk behaviour of the exchange rate. They argue that the exchange rate can be expressed as the discounted sum of the current observable and unobservable fundamentals, and has the following form:

$$s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t(f_{1,t+j} + v_{1,t+j}) + b\sum_{j=0}^{\infty} b^j E_t(f_{2,t+j} + v_{2,t+j}), \qquad (2.5)$$

where s is the log of the exchange rate, b is the discount factor, f collects the observable fundamentals, and v the unobservable fundamentals while the 'no-bubbles' condition for the expected spot exchange rate is assumed. They show that, if at least one forcing fundamental is I(1) and the discount factor is close to 1, then the exchange rate will move approximately like a random walk, while the correlation between exchange rate returns and changes of the macro fundamentals is very small. Their second finding, which is our main motivation in this chapter, comes from the Granger-causality analysis. Their in-sample analysis provides evidence that nominal exchange rate changes Granger-cause the macro fundamentals and this causality is much stronger than the other way around. Hence, they reach the conclusion that there is a link between them, such that the exchange rates can help forecasting the macroeconomic fundamentals.

Largely inspired by the second finding of EW05, we extend their work and we forecast the major macroeconomic fundamentals (output gap, inflation, and real exchange rate) by building an out-of-sample real-time forecasting exercise employing a TVP-BVAR model.[7] More specifically, we use the Taylor rule-based forecasting

[7] As Rossi (2013b) mentions, the empirical evidence of in-sample predictability does not necessarily equate to out-of-sample predictability. The usual method for testing in-sample predictability is by

model as in Molotdsova and Papell (2009). To do so, we use equation (2.4) as the monetary policy for the home country (U.S.) and the same for the foreign country (U.K.) incorporating the real exchange rate (q_t) as well. So, we can re-write the policy rule:

$$\text{Home country: } i_t = \lambda + \alpha_\pi \pi_t + \beta_y y_t^{gap} + \rho i_{t-1} + \varepsilon_t, \tag{2.6}$$

where $\alpha_\pi = (1-\rho)\kappa$, $\beta_y = (1-\rho)\beta$ and $\lambda = (1-\rho)\delta$. Regarding the foreign country:

$$\text{Foreign country: } i_t^f = \lambda^f + \alpha_\pi^f \pi_t^f + \beta_y^f y_t^{fgap} + \gamma_q^f q_t^f + \rho^f i_{t-1}^f + \varepsilon_t^f, \tag{2.7}$$

where *f* denotes the terms of the foreign country, $\gamma_q^f = (1-\rho^f)\zeta$ and q_t^f is the real exchange rate of the foreign country assuming that this country is targeting the Purchasing Power Parity (PPP) level of the exchange rate (Molotdsova and Papell, 2009).[8] Hence, to derive the Taylor rule-based forecasting equation, the interest rate reaction function of the foreign country is subtracted from that of the home country. Assuming that the uncovered interest rate parity (UIP) holds, $\mathrm{E}_t(\Delta s_{t+1}) = (i_t - i_t^f)$, the following forecasting equation is derived:[9]

$$\Delta s_{t+1} = \omega + a_\pi \pi_t - \alpha_\pi^f \pi_t^f + \beta_y y_t^{gap} - \beta_y^f y_t^{fgap} - \gamma_q^f q_t^f + \rho i_{t-1} - \rho^f i_{t-1}^f + u_{t+1}, \tag{2.8}$$

where $\omega = (\lambda - \lambda^f)$ and u_{t+1} is the error term. Equation (2.8) is our starting point. In other words, we incorporate this theory-based model into a vehicle that will allow us to forecast the Taylor rule fundamentals. We decide that the vehicle should be a VAR model since this can develop and elaborate theory-based simultaneous forecasting equations. First of all, VARs have become the workhorse model for multivariate analysis and for macroeconomic forecasting exercises since the pioneering work of Sims (1980). Some features of this vehicle are its simplicity, flexibility and ability to fit

estimating the model in hand and then conducting a traditional Granger-causality test, checking the significance of the estimated parameters using a simple t-test. On the other hand, out-of-sample predictability is tested by splitting the sample into two parts. The in-sample part is used for estimations and to generate forecasts, while the out-of-sample part is used to evaluate them using the appropriate loss functions.

[8] The real exchange rate is defined as the nominal FX rate plus the foreign price level minus the home price level, where variables are in natural logarithms.

[9] Linking the interest rate differential with the exchange rates is discussed by Molodtsova and Papell (2009). As noted, any circumstance causing the central bank to increase the interest rate will lead to a future depreciation of the home currency. However, Chinn (2006) states that UIP does not hold in the short run and this is known as the 'forward premium puzzle'. Other explanations for the failure of UIP are given by Gourinchas and Tornell (2004) and Einchenbaum and Evans (1995).

the data through the rich over-parameterisation that entails the danger of imprecise inference and failure to summarise the dynamic correlation patterns among the observables and their future paths, leading to poor forecasts. ‘Shrinkage’ has been the solution to this over-fitting problem, by imposing *prior* constraints and beliefs on the model’s parameters, (see, for example, the Minnesota prior used by Litterman (1979) and Doan et al. (1984)). Bayes’ theorem then provides the optimal way of combining all the available information coming from the data and the prior beliefs leading to the posterior inference and probably more accurate predictions.

As discussed in the previous section, Taylor rule relationships suffer from structural changes and non-linearities. So, for the purpose of our forecasting exercise, we employ a time-varying parameters Bayesian VAR model (TVP-BVAR), in order to account for the changes in the monetary policy rules over time. This kind of model assumes a constant covariance matrix (homoscedastic TVP-BVAR) and treats all the variables as endogenous. Similar heteroscedastic TVP-BVAR models, where the time variation derives from both parameters and the variance-covariance matrix of the models’ innovations, have been used in Primiceri (2005) and D’Agostino et al. (2013), while the homoscedastic models have been used by Sarantis (2006) and Byrne et al. (2016).

Hence, for our forecasting exercise, a homoscedastic TVP-BVAR model as in Korobilis (2013) has been selected. Keeping Korobilis’s (2013) notation, the reduced form TVP-BVAR can be written in the following linear specification:

$$y_t = c_t + B_{1,t} y_{t-1} + B_{2,t} y_{t-2} + ... + B_{p,t} y_{t-p} + u_t \, , \tag{2.9}$$

where p is the number of lags, y_t is an $m\times1$ vector of $t = t,...,T$ observations of the dependent variables, B matrices collect the coefficients, errors $u_t \sim N_m(0,\Sigma)$ where Σ is a constant covariance matrix of $m\times m$ dimensions and m is the number of variables. Re-writing the model in a linear state-space form:

$$y_t = z_t \beta_t + \varepsilon_t \tag{2.10}$$

$$\beta_t = \beta_{t-1} + \eta_t \tag{2.11}$$

equation (2.10) is the measurement equation where $z_t = I_m \otimes x_t = I_m \otimes \left(1, y_{t-1},..., y_{t-p}\right)'$ is an $m \times n$ matrix, $n = mk$ and $k = mp + 1$. Equation (2.11) is the driftless random walk state equation of the parameters, β_t is an $n \times 1$ state vector $\left[c_t^{'}, vec\left(B_{1,t}^{'}\right), ..., vec\left(B_{p,t}^{'}\right)\right]'$ of parameters, $\eta_t \sim N(0, Q)$, where Q is an $n \times n$ covariance matrix, and $\varepsilon \sim N(0, \Sigma)$, where Σ is an $m \times m$ covariance matrix of the model. It is assumed that η_t and ε_t are not correlated at all lags and leads. Kim and Nelson (1999) show how TVP models can be expressed in a state-space form and how the unobserved states of the time-varying parameters can be estimated via the Kalman filter.

As discussed earlier, we want to bring the theory-based model (eq. 2.8) into the TVP-BVAR vehicle, which will allow us to forecast the Taylor rule fundamentals. Therefore, the vector of dependent variables of our model is represented by: $Y_t = \left[\Delta s_t, y_t^{gap}, y_t^{fgap}, \pi_t, \pi_t^{f}, q_t^{f}, i_{t-1}, i_{t-1}^{f}\right]'$, where ($\Delta s$) is the nominal exchange rate change, (y^{gap}) is the output gap, (π) is the inflation rate, (q) is the real exchange rate, and (i) is the nominal interest rate set by the monetary authorities (with a period lag due to the gradual adjustment to the target level). In order to investigate the predictive content of the exchange rates, we want to allow a priori only the exchange rate changes to give their predictive power, along with the first own lag of each dependent variable. The Bayesian approach treats all coefficients as random variables by assigning a prior distribution to them and allowing the data likelihood to determine their posterior values. So, we decide to assign an uninformative normal prior for the constants and the fundamentals that we allow them to a priori predict, and a very tight normal prior for the predictors that we want to restrict.

Priors

Regarding the random walk transition equation, we practically need to set the initial condition (starting values for the Kalman filter) of β_t. According to Korobilis (2013), priors for the parameters do not need to be specified in every time period since this is implicitly defined recursively as $\beta_t \sim N(\beta_{t-1}, Q)$. Given the purpose of our forecasting exercise, we use a non-informative normal prior of $\beta_0 \sim N(0, 10^2)$ for the variables that we allow to draw predictive power, and a tight normal prior of $\beta_0 \sim N(0, 0.01^2)$ for those that we want to restrict. As regards the Σ (covariance of the VAR model), an inverse Wishart prior has been set as: $\Sigma \sim IW(\underline{J}^{-1}, \underline{v})$, with non-informative hyperparameters $(\underline{J} = \underline{v} = 0)$, where J is the scale matrix and v is the degrees of freedom as in Koop and Korobilis (2009). For the covariance matrix Q, we impose an inverse Wishart prior, $Q \sim IW(\underline{R}^{-1}, \underline{\xi})$, where $\underline{\xi} = (n+1)2$ is the degrees of freedom (n is the number of parameters in the state vector) and $\underline{R} = k_R I_n$, where k_R is the scaling factor and equal to 0.0001, as used in Primiceri (2005). Cogley and Sargent (2002) suggest that this kind of scaling factor should be used, since time-varying parameters should vary smoothly and not change sharply over time. Details about the posterior distributions, the Kalman filter, and the smoothing process can be found in Appendix B.

As a standard practice in the forecasting exercises, we also employ a BVAR(1) model with the so-called Minnesota prior (Doan et al. 1984) and a standard VAR(1) model estimated via OLS to forecast the macro-fundamentals, while all the aforementioned candidate models are compared with the driftless random walk benchmark model. We use 1 number of lags, as BIC recursively suggests. Details about the BVAR specification and the Minnesota prior can be found in Appendix B.

2.4 Data and real-time forecasting exercise

It is well known that data such as output, price level indices, money stock, and others, are continuously revised by statistical offices due to changes in the definition of the variables (e.g. GNP to GDP), or just because statistical agencies have acquired additional information and current data are being updated. Hence, a real-time dataset is an important ‘tool’, especially for researchers who conduct out-of-sample forecasting exercises. Among others, Croushore and Stark (2001), Croushore (2006), Orphanides (2001, 2003), Molodtsova and Papell (2009), and Faust, Rogers and Wright (2003) have studied the importance of using real-time data in several forecasting and estimation exercises and conclude that the predictive ability of the forecasting model is enhanced by using real-time data. Also, Clements (2012) pinpoints the fact that findings about predictors’ content may be misleading when fully revised data are used instead. Hence, we carry out a real-time forecasting exercise that uses vintage data that were available to the forecaster only at the time he was making the forecasts.[10] Variables such as nominal exchange rates and nominal interest rates are never revised.

We use quarterly data from 1971:Q2 to 2012:Q3 for the two countries (U.S. and U.K.). The real GDP (seasonally adjusted) is used as a proxy for the U.S. output, extracted from the Fed of Philadelphia, and for the real GDP of U.K., data extracted from the ONS. For both countries, the output gap is measured using the HP filter. Before we apply the filter, we backcast and forecast our data by 12 datapoints with an AR(4) model. As regards the inflation rate, we compute it as π_t = *GDP deflator*$_t$ – *GDP deflator*$_{t-4}$ (GDP deflator in natural logs). For the data that is not revised, we use the Pacific Exchange Rate Service website to extract the nominal USD/GBP exchange rate.[11] We calculate the real GBP/USD exchange rate as the nominal GBP/USD exchange rate plus the log of the U.S. price level minus the log of the U.K. price level. The USD/GBP exchange rate is defined as the U.S. dollar price of a British pound.

Regarding the interest rates, it would not be wise to use the effective Federal fund rate and the Official Bank rate as a proxy for the nominal interest rates since both figures hit the zero lower bound (ZLB) at the end of 2008. Instead, there are studies that suggest the long-term interest rates as an alternative monetary policy instrument. McCough et al. (2005) characteristically mention that the long-term rates might be a physical substitute as they are highly related to the future expected path of the short-term interest rates, while Jones and Kulish (2013) show that long-term rates are good instruments for conducting monetary policy and sometimes performing better than the standard Taylor rules. Also, Chinn and Meredith (2004) provide empirical evidence to show that testing UIP model using interest rates on longer-maturity bonds, leads to better in-sample results consistent with the UIP theory. On the other hand, Wu and Xia (2016) construct a new measure called shadow rate, approximating the effective Federal fund rate. By using a Gaussian affine term structure model, they generate a shadow rate allowed for taking negative values, and replace the federal fund rate time-series with this shadow rate for the period where economy is at the ZLB. They find that this shadow rate is highly correlated with the federal fund rate before 2009, interacting with the macro fundamentals in the same manner as federal fund rate did with them historically. In this

[10] We should note that in real-time datasets there is always one period lag between the vintage date and the last observation of that vintage. So, assuming, for example, the 2000:Q1 vintage, the last observation of that vintage is at 1999:Q4.
[11] The Pacific Exchange Rate Service's website can be found at: http://fx.sauder.ubc.ca/data.html.

study we opt to use the 10-year Treasury bond rates as a proxy for the nominal interest rates.

2.4.1 Forecast implementation and evaluation

For the out-of-sample forecasting exercise, we consider the recursive scheme along with the rolling scheme as a robustness check. In the recursive scheme, the model is estimated for the period 1971:Q2–1989:Q4 (using data from the 1990:Q1 vintage) and iterated forecasts are generated and stored for h periods ahead, where h =1-, 2-, 3-, and 4-quarters-ahead horizon. Then, data in vintage 1990:Q2 is used and the model is re-estimated again, with forecasts for h periods ahead being computed again. This process is repeated until the whole dataset is exhausted. We explore the robustness of our results with respect to different forecasting scheme. Hence, the rolling scheme is also used, where estimations of the model are made with a fixed-size rolling window, which we choose to set at 15 years (i.e. 61 most recent observations available at the time we conduct the forecasts).

According to D'Agostino et al. (2013) and Korobilis (2013), if we rewrite our model in the form below, we can derive the standard forecasting formula using the iterative method. So, given the companion form of our TVP-BVAR model:

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_t\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t \ ,$$

where $\mathbf{y}_t = \left[y_t' .... y_{t-p+1}'\right]'$, $\boldsymbol{\varepsilon}_t = \left[\varepsilon_t', 0, ..., 0\right]'$, $\mathbf{c}_t = \left[c_t', 0, ..., 0\right]'$ and $\mathbf{B}_t = \begin{bmatrix} B_{1,t} ... B_{p-1,t} & B_{p,t} \\ I_{m(p-1)} & 0_{m(p-1)\times m} \end{bmatrix}$,

then iterated h-step ahead forecasts can be obtained according to the following formula:

$$E(\mathbf{y}_{t+h}) = \sum_{i=0}^{h-1} \mathbf{B}_t^{\mathbf{i}}\, \mathbf{c}_t + \mathbf{B}_t^{h}\, \mathbf{y}_{t-1} \ . \tag{2.12}$$

Following Korobilis (2013), we plug into the above formulas the values of the last known coefficients in sample $\left(\hat{\beta}_T\right)$.

It is a standard practice to evaluate the performance of a forecasting model using the root mean square forecast error (RMSFE) and the mean absolute forecast error (MAFE). The first statistic takes the difference between the forecast (f) and the corresponding observed (A) value as a squared term, and the square root is taken and averaged over the total out-of-sample period. The second method measures the magnitude of the forecast error, where absolute values are taken and averaged over the full forecasting period.

$$RMSFE^{h} = \left\{ \frac{\sum_{t=\tau_0}^{\tau_1 - h} \left(f_{t+h|t} - A_{t+h} \right)^2}{\tau_1 - h - \tau_0 + 1} \right\}^{1/2}, \tag{2.13}$$

$$MAFE^{h} = \frac{\sum_{t=\tau_0}^{\tau_1 - h} \left| \left(f_{t+h|t} - A_{t+h} \right) \right|}{\tau_1 - h - \tau_0 + 1}, \tag{2.14}$$

where τ_0 corresponds to the last observation of the in-sample period and τ_1 is the end of the forecasting period. Our forecasts are compared with the corresponding figure observations published the next quarter vintage. Most of the time, we are interested in reporting the relative RMSFE and the relative MAFE by dividing the RMSFE and the MAFE of the candidate forecasting model by those of the benchmark forecasting model. The benchmark model that we choose for all the variables is the driftless random walk (RW). The same benchmark model has been used by Korobilis (2013), who forecasts the U.K. inflation, unemployment, and interest rate. The driftless RW assumes that $E_t\left(y_{t+h} - y_t\right) = 0$ and produces the h-step ahead forecast of $\hat{y}_{t+h|t} = y_t$. This yields a forecast error $fe_{t+h|t}^{RW} = \hat{y}_{t+h|t} - y_{t+h}^{o} = y_t - y_{t+h}^{o}$, where y_{t+h}^{o} is what we observe (realisation) at $t+h$. Another standard practice in the forecasting literature is to test whether the candidate model produces significantly lower MSFE than the benchmark model using the one-sided test proposed by Clark and West (2006, 2007) (hereafter CW). In other words, it tests whether the forecasting ability of the two nested models is the same (in terms of MSFE), against the alternative that the candidate model generates better forecasts. This test can be applied using either a recursive or a rolling scheme. The test statistic can be found in Appendix A.

2.5 Empirical results

The following tables report the relative RMSFE and MAFE, where a ratio below 1 denotes that the candidate model (TVP-BVAR, BVAR or VAR) outperforms the benchmark model in out-of-sample accuracy. The CW test is also reported in the following tables at different levels of significance. The results of the recursive scheme are reported first, and then robustness is checked using the rolling estimation scheme.

Recursive scheme

Table 2.3 presents the results of the forecasts' evaluation based on the RMSFE. In seven out of 20 cases, TVP-BVAR outperforms the RW, while in only two cases, BVAR and VAR forecast better than the benchmark. More specifically, the TVP model improves upon the RW when forecasting the U.S. output gap at all horizons, the U.K. output gap for 3- and 4-quarters-ahead, and the U.K. real exchange rate at 1-period-ahead. For the majority of these cases, the results are highly significant, as the CW test indicates.

Table 2.3: Relative RMSFE of candidate models for h = 1, 2, 3 and 4 periods ahead

	RW RMSFE	TVP-BVAR(1) -RW ratio	BVAR(1) - RW ratio	VAR (1) - RW ratio
y_{t+1}^{gap}	0.0026	**0.75*****	1.69	1.77
y_{t+2}^{gap}	0.0046	**0.84*****	1.63	1.70
y_{t+3}^{gap}	0.0063	**0.90*****	1.54	1.58
y_{t+4}^{gap}	0.0076	**0.95****	1.42	1.46
y_{t+1}^{fgap}	0.0031	1.14	1.61	1.65
y_{t+2}^{fgap}	0.0054	1.01	1.59	1.62
y_{t+3}^{fgap}	0.0075	**0.99**	1.50	1.54
y_{t+4}^{fgap}	0.0092	**0.97***	1.41	1.44
π_{t+1}	0.0032	1.14	1.07	1.08
π_{t+2}	0.0047	1.12	1.10	1.11
π_{t+3}	0.0059	1.06	1.12	1.13
π_{t+4}	0.0071	1.11	1.16	1.16
π_{t+1}^{f}	0.0115	1.08	1.06	1.09
π_{t+2}^{f}	0.0129	1.10	1.21	1.26
π_{t+3}^{f}	0.0134	1.08	1.34	1.39
π_{t+4}^{f}	0.0160	1.07	1.21	1.26
q_{t+1}^{f}	0.0434	**0.96****	**0.98**	**0.98***
q_{t+2}^{f}	0.0698	1.01	1.01	1.02
q_{t+3}^{f}	0.0848	1.02	1.00	1.01

q_{t+4}^{f}	0.0928	1.02	**0.98**	**0.98**
No. of ratios < 1		**7**	**2**	**2**

Notes: The above results are obtained via recursive estimations. The first column shows the RMSFE of the driftless random walk. The second, third and fourth columns report the relative RMSFE, where a ratio less than 1 (in **bold**) indicates that the candidate model generates lower RMSFE than the RW. Asterisks indicate that the null hypothesis of equal predictive accuracy (one-sided CW test) is rejected against the alternative of outperforming the benchmark model at the 1% (***), 5% (**) and 10% (*) significance levels. The superscript *f* denotes the variables of the U.K., while the rest fundamentals belong to the U.S.

The results for the U.S. inflation are pessimistic, with the RW model always generating lower RMSFE than our model. Stock and Watson (2007, 2008) admit that inflation is difficult to forecast, especially in large samples. Nevertheless, they show that a backward-looking Phillips curve (with autoregressive distributed lag – *ADL* specification) delivers better inflation forecasts than an AR(AIC) model for the U.S. in both short and long horizons, although these results are heavily sample dependent. Also, the Bayesian model averaging models used by Wright (2009) and Nikolsko-Rzhevskyy (2011), and the TVP-BVAR model with stochastic volatility used by D'Agostino et al. (2013), clearly outperform the random walk at any horizon when forecasting the U.S. inflation rate. Regarding the forecasting performance of the BVAR(1) and VAR(1) models, predictions look very poor compared to the benchmark model. Using the relative MAFE, the results remain somewhat the same, as reported in Table 2.4.

Table 2.4: Relative MAFE of candidate models for h = 1, 2, 3 and 4 periods ahead

	RW MAFE	TVP-BVAR(1) -RW ratio	BVAR(1) - RW ratio	VAR (1) - RW ratio
y_{t+1}^{gap}	0.0019	**0.75**	1.80	1.87
y_{t+2}^{gap}	0.0035	**0.84**	1.76	1.82
y_{t+3}^{gap}	0.0048	**0.88**	1.63	1.68
y_{t+4}^{gap}	0.0060	**0.91**	1.49	1.53
y_{t+1}^{fgap}	0.0022	1.12	1.72	1.76
y_{t+2}^{fgap}	0.0038	1.01	1.79	1.84
y_{t+3}^{fgap}	0.0054	**0.98**	1.73	1.78
y_{t+4}^{fgap}	0.0065	**0.95**	1.69	1.73
π_{t+1}	0.0025	1.05	1.06	1.07
π_{t+2}	0.0037	1.09	1.10	1.11
π_{t+3}	0.0048	1.04	1.11	1.11
π_{t+4}	0.0058	1.10	1.14	1.14
π_{t+1}^{f}	0.0071	1.08	1.13	1.16
π_{t+2}^{f}	0.0087	1.09	1.28	1.34

π_{t+3}^{f}	0.0089	1.08	1.50	1.57
π_{t+4}^{f}	0.0102	1.06	1.38	1.43
q_{t+1}^{f}	0.0285	**0.95**	1.01	1.03
q_{t+2}^{f}	0.0472	1.00	1.07	1.09
q_{t+3}^{f}	0.0616	1.01	1.05	1.05
q_{t+4}^{f}	0.0695	1.02	1.00	1.00
No. of ratios < 1		**7**	**0**	**0**

Notes: The above results are obtained via recursive estimations. The first column shows the MAFE of the driftless random walk. The second, third, and fourth columns report the relative MAFE, where a ratio less than 1 (in **bold**) indicates that the candidate model generates lower MAFE than the RW. The superscript *f* denotes the variables of the U.K., while the remaining fundamentals belong to the U.S.

Rolling scheme as a robustness check

We check the robustness of the above results using a different estimation scheme. The models are now estimated using a fixed-size rolling window of the 61 most recent observations (quarters), resulting in findings with little difference relative to the recursive scheme. Using the RMSFE, the number of cases with a relative ratio of less than 1 is eight out of 20 for the TVP-BVAR model, while the results for the remaining models do not seem to change much.

Table 2.5: Relative RMSFE of candidate models for h = 1, 2, 3 and 4 periods ahead

	RW RMSFE	TVP-BVAR(1) -RW ratio	BVAR(1) - RW ratio	VAR (1) - RW ratio
y_{t+1}^{gap}	0.0026	**0.89*****	1.62	1.87
y_{t+2}^{gap}	0.0046	**0.89*****	1.56	1.84
y_{t+3}^{gap}	0.0063	**0.92****	1.51	1.79
y_{t+4}^{gap}	0.0076	**0.93****	1.47	1.72
y_{t+1}^{fgap}	0.0031	1.12	1.41	1.52
y_{t+2}^{fgap}	0.0054	1.03	1.48	1.65
y_{t+3}^{fgap}	0.0075	1.05	1.47	1.66
y_{t+4}^{fgap}	0.0092	1.03	1.42	1.60
π_{t+1}	0.0032	1.02	1.12	1.15
π_{t+2}	0.0047	1.04	1.18	1.22
π_{t+3}	0.0059	1.02	1.20	1.23
π_{t+4}	0.0071	1.08	1.20	1.22
π_{t+1}^{f}	0.0115	**0.99**	**0.93****	**0.96**
π_{t+2}^{f}	0.0129	1.00	**0.98****	1.03
π_{t+3}^{f}	0.0134	**0.98***	1.02	1.08
π_{t+4}^{f}	0.0160	**0.97**	**0.97****	1.02

q_{t+1}^{f}	0.0434	**0.96****	1.02	1.08
q_{t+2}^{f}	0.0698	1.04	1.11	1.20
q_{t+3}^{f}	0.0848	1.08	1.19	1.29
q_{t+4}^{f}	0.0928	1.08	1.22	1.33
No. of ratios < 1		**8**	**3**	**1**

Notes: The above results are obtained via rolling estimations. The first column shows the RMSFE of the driftless random walk. The second, third and fourth columns report the relative RMSFE, where a ratio less than 1 (in **bold**) indicates that the candidate model generates lower RMSFE than the RW. Asterisks indicate that the null hypothesis of equal predictive accuracy (one-sided CW test) is rejected against the alternative of outperforming the benchmark model at the 1% (***), 5% (**) and 10% (*) significance levels. The superscript *f* denotes the variables of the U.K., while the remaining fundamentals belong to the U.S.

Table 2.6: Relative MAFE of candidate models for h = 1, 2, 3 and 4 periods ahead

	RW MAFE	TVP-BVAR(1) -RW ratio	BVAR(1) **-** RW ratio	VAR (1) **-** RW ratio
y_{t+1}^{gap}	0.0019	**0.85**	1.61	1.84
y_{t+2}^{gap}	0.0035	**0.88**	1.50	1.72
y_{t+3}^{gap}	0.0048	**0.89**	1.40	1.61
y_{t+4}^{gap}	0.0060	**0.90**	1.31	1.50
y_{t+1}^{fgap}	0.0022	1.08	1.48	1.61
y_{t+2}^{fgap}	0.0038	1.09	1.53	1.71
y_{t+3}^{fgap}	0.0054	1.11	1.52	1.69
y_{t+4}^{fgap}	0.0065	1.10	1.54	1.71
π_{t+1}	0.0025	**0.98**	1.11	1.13
π_{t+2}	0.0037	1.02	1.15	1.18
π_{t+3}	0.0048	1.02	1.15	1.18
π_{t+4}	0.0058	1.08	1.16	1.19
π_{t+1}^{f}	0.0071	1.00	**0.96**	1.00
π_{t+2}^{f}	0.0087	**0.98**	**0.97**	1.01
π_{t+3}^{f}	0.0089	**0.98**	1.09	1.17
π_{t+4}^{f}	0.0102	**0.99**	1.10	1.15
q_{t+1}^{f}	0.0285	**0.96**	1.11	1.22
q_{t+2}^{f}	0.0472	1.06	1.16	1.25
q_{t+3}^{f}	0.0616	1.08	1.16	1.25
q_{t+4}^{f}	0.0695	1.08	1.17	1.27
No. of ratios < 1		**9**	**2**	**0**

Notes: The above results were obtained via rolling estimations. The first column shows the MAFE of the driftless random walk. The second, third, and fourth columns report the relative MAFE, where a ratio less than 1 (in **bold**) indicates that the candidate model generates lower MAFE that the RW. The superscript *f* denotes the variables of the U.K., while the remaining fundamentals belong to the U.S.

The main finding of this robustness check is that, in both schemes, the TVP-BVAR model significantly outperforms the random walk at all horizons when forecasting the U.S. output gap, while under the rolling scheme, our model generates good forecasts for the U.K. inflation at 3- and 4-quarters-ahead horizons. As regards the U.K. inflation, Clausen and Clausen (2010) find that the backward-looking Phillips curve is able to outperform the AR(1) model only at 8- and 12-quarters-ahead horizons, while Korobilis (2013) find that a TVP-BVAR(4) model with variable selection technique generates better forecasts than the driftless random walk.

2.6 Conclusions

The noteworthy empirical findings of Engel and West (2005) have been our starting point and motivation, while the extension of their work is our contribution to the literature on international macroeconomics. Although EW05 characterise their evidence as *modest*, they argue that exchange rate changes are likely to be useful in forecasting the Taylor rule fundamentals. They focus on in-sample evidence, conducting Granger-causality tests with revised data in a stable environment without structural changes, and they do find that exchange rates Granger-cause the macroeconomic fundamentals compared to a far weaker causality from the fundamentals to the exchange rates. Our work contributes to the literature by building a real-time out-of-sample forecasting exercise in an attempt to investigate whether the exchange rate changes incorporate useful information in predicting the Taylor rule fundamentals. We pay special attention to the structural changes that interest rate reaction functions present by applying a mechanism that allows for time-variation in the parameters of the VAR model. In addition, we use real-time data for the output and the price index rather than revised data that EW05 use.

By drawing a priori more predictive power from the nominal exchange rate changes, we conclude that the TVP-BVAR model is able to generate accurate real-time forecasts for the U.S. output gap at all horizons, the U.K. output gap at the 3- and 4-quarter-ahead horizons and the U.K. real exchange rate at 1-quarter-ahead, as well as the U.K. inflation using rolling estimations. Our results also underline the fact that taking into account the structural changes is important for forecasting. Finally, we conclude that the finding of EW05 can be supported by this out-of-sample exercise, and so further research analysing the behaviour and predictive content of the nominal exchange rates may be useful.

Chapter 3

Forecasting the Nominal Exchange Rate Movements in a Time-varying Environment: The Case of the U.S. and the U.K.

3.1 Introduction

This chapter revisits one of the long-standing puzzles in international economics stemming from the findings of Meese and Rogoff (1983a, 1983b), that macroeconomic fundamentals are weak predictors of the exchange rate movements, especially at the short horizon.[12] In fact, the literature suggests that the a-theoretical random walk model without drift appears to be the most successful model in forecasting out-of-sample the nominal exchange rates. This exchange rate disconnect puzzle has been researched by many researchers and practitioners for the last three decades, and many macroeconomic models and econometric techniques have been developed in an attempt to outperform this naïve model. A critical survey by Rossi (2013a) supports the view that exchange rate predictability depends on several factors, such as the choice of the predictors, the forecasting model (TVP, linear or non-linear), econometric technique, forecast horizon, estimation scheme, data frequency, forecast evaluation method, and finally whether we are dealing with in-sample or out-of-sample predictability. So, what we observe in the literature is different studies focusing on different sets of the above factors, while the goal is always the same, to outperform the driftless random walk model, which seems to be the toughest benchmark model in the exchange rate forecasting literature.

In this chapter, we examine the potential causes of the currency disconnect puzzle, employing a real-time out-of-sample forecasting race between several fundamentals-based models proposed in the literature and the benchmark random walk model. The predictors that we employ are motivated by fundamentals-based models, while a number of these models are well known from earlier research. These are the UIP model, the PPP model, the Monetary model and the Term-Structure Forward Premium model

[12] The analysis of this chapter is based on Promponas and Peel (2016).

(see, e.g. Clark and West, 2006; Clarida and Taylor, 1997; Cheung et al., 2005). In the last decade, Taylor rule fundamentals have also been used as predictors for the future exchange rate changes (see, e.g. Engel and West, 2005, 2006; Molodtsova and Papell, 2009). This forecasting equation follows the monetary policy's principles as set in Taylor (1993) and presented analytically in the previous chapter. We place great emphasis on the possible non-linearities of the exchange rate forecasting models caused by the time-varying relationship between exchange rates and fundamentals, as well as on the relevance of the predictors that may potentially change over time. Time-variation, as a special form of non-linearity (Rossi, 2013a), and parameters' instability have drawn the attention of many studies (see Sarantis, 2006; Clarida et al., 2003; Baillie and Kilic, 2006; Mark and Moh, 2002; Byrne et al., 2016, forthcoming) mainly due to the unstable macroeconomic conditions, the monetary policy shifts, asymmetric preferences, and the weak rational expectation where agents are not fully informed about the economy and the monetary authorities' intervention in the exchange rate targeting policy, especially at the short horizon (Mark and Moh, 2002). This unstable and sometimes weak connection between currencies and fundamentals is also explained in Bacchetta and van Wincoop (2004, 2013) using the 'scapegoat theory', where observed variables are assigned more weight (and become scapegoats) when exchange rate fluctuations are mainly driven by the unobserved macroeconomic shocks. Fratzscher et al. (2015) refer to it as a 'rational confusion' of the exchange rate market agents who interpret the true parameters of the model conditioning only on the observed predictors at times when the exchange rate fluctuates in response to the unobservables. Hence, taking into account the scapegoat fundamentals and time-varying weights assigned to them, may be helpful in an out-of-sample exchange rate (FX) forecasting exercise.

In order to investigate whether the forecasting performance of our models is improved or not when considering these potential instabilities, we employ both linear and non-linear econometric vehicles in our exercise. We use a BVAR model, a homoscedastic TVP-BVAR model, which allows for the coefficients to change over time, a heteroscedastic TVP-BVAR model, accounting for time-variation in both parameters and innovations, and finally Bayesian dynamic model averaging and selection (DMA, DMS) models, which not only allow for the parameters and covariance to change over time, but also for the entire set of predictors to switch over time. TVP models similar to these have been recently used in the exchange rate forecasting literature, exhibiting a relevant out-of-sample success (see Byrne et al., 2016; Sarantis, 2006), and other studies using non-linear smooth transition regressions (STR) and regime-switching models (see Sarno et al., 2006; Clarida et al., 2003). Bayesian and time-varying approaches have become topical in the forecasting literature, and we believe that this is a good opportunity to empirically test the predictive performance of these econometric models in this challenging research area.

Apart from the fundamentals-based models discussed above, we also novelly include an open-economy new Keynesian dynamic stochastic general equilibrium (DSGE) model in our forecasting exercise. The literature on nominal exchange rate forecasting does not reflect these structural models. In the last decades, DSGE models have become an empirical tool for the central banks and other policy-making institutions, which rely heavily on them for forecasting inflation, output gap and other macroeconomic variables since they may help in the decision-making process. We therefore use a richly specified DSGE model following Gali and Monacelli (2005), Justiniano and Preston (2010) and Alpanda et al. (2011), estimated with Bayesian likelihood methods, as used in An and Schorfheide (2007a), to compete with the naïve benchmark in out-of-sample accuracy.

We also use vintage data for the variables that suffer from consecutive revisions (GDP, price level, money stock, etc.), while, as discussed in the previous chapter, evidence from the literature suggests that the forecasting performance of models is increased when data that are available at the time that agents are making forecasts are used (see Orphanides, 2001; Croushore and Stark, 2001; Croushore, 2006).[13] We use a recursive estimation scheme in forecasting the nominal FX returns for the 1-, 2- and 3-quarters-ahead periods, while forecasts are evaluated using the relative RMSFE and the Clark and West (2006, 2007) (CW) one-sided test of predictive superiority, as in the previous chapter. Once again, we consider the U.S. as the home country and U.K. as the foreign country. We select these countries mainly due to the availability of complete

[13] More recently, Molodtsova et al. (2008), Molodtsova and Papell (2009), and Nikolsko-Rzhevskyy (2011) refer to the importance of using real-time (vintage) data in forecasting exercises using several exchange rate models. Real-time data in the forecasting literature has become increasingly important and crucial and, therefore, it is necessary for our study, although lack of real-time databases and data limitations are deterrents.

and well-structured real-time databases, given the data requirements and the large number of variables that we employ in this study.

This paper is organised as follows: Section 2 provides a critical review of the literature for both theoretical and empirical exchange rate models and their characteristic findings for the sake of completeness. Section 3 presents the specifications of the time-varying and non-time-varying econometric models and the DSGE model. Section 4 summarises the forecasting models and discusses the data details, forecasts implementation and evaluation methods. Section 5 analyses the out-of-sample forecasting race results and provides a discussion of the forecasting performance of each model. Also, a sensitivity analysis is conducted for robustness purposes. Section 6 concludes the study, outlining the main empirical findings.

3.2 Exchange rate models and predictors

The most commonly used predictors in the exchange rate forecasting literature are the interest rate, real output, output gap, price level, money supply, forward premium, and unemployment level. In this section, we present the relevant models that we use in this chapter, along with a discussion of their successfulness from a critical point of view. This may offer the reader a wider picture of the literature as well as an understanding of what we have learnt about exchange rate forecasting so far.

Model 1. Random walk without drift (RW)

The random walk model without drift is a naïve a-theoretical model, which represents the benchmark model in this analysis. If the natural log of the exchange rate is denoted by s_t (measured as the home price for a unit of the foreign currency), E_t (.) the expectation at time t and horizon h, then the model predicts:

$$E_t(s_{t+h} - s_t) = 0 . \qquad (3.1)$$

The vast majority of studies in the literature compare forecasting models with the above specification as studies such as Engel et al. (2008) and Engel and Hamilton (1990) have tested both random walk with and without drift and find that driftless random walk delivers better results.

Model 2. Uncovered interest rate parity (UIP)

This is Fisher's (1896) UIP model, where the expected change of the exchange rate should be equal to the interest rate differential, or the gain from holding that currency should counterbalance the opportunity cost and risk of holding money in this currency. This can be written as:

$$E_t(s_{t+h} - s_t) = a + \beta(i_t - i_t*) + u_{t+h}\,, \tag{3.2}$$

where s_t is the logarithm of the spot exchange rate, i_t is the nominal interest rate, and also $\alpha = 0$ and $\beta = 1$. Empirical findings from studies that use the interest differential as predictor are not very positive. Clark and West (2006) report predictability only for one out of four FX rates considered and only for the short horizon (one month ahead). Somewhat moderate results are presented by Molodtsova and Papell (2009), where the UIP model is estimated without any sign restriction and they find predictability only for Australia and Canada out of twelve countries when a constant is included in the regression, and for Australia, Canada, Japan and Switzerland when it is not. Cheung et al. (2005) contribute to longer-horizon predictability, providing empirical support for the 20-quarters ahead horizon compared to the disappointing results for the short horizons. Similar findings for long-horizon predictability come from Alquist and Chinn (2008), while Chinn and Meredith (2004) also find strong long-horizon in-sample predictability.

Model 3. Forward premium term structure (FPTS)

There is a consensus within the literature that the risk-neutral efficient market hypothesis has been rejected (see Hodrick, 1987; Taylor, 1995; Chinn and Meredith, 2004; Chinn, 2006), while the most common empirical method for testing this hypothesis is to estimate the Fama (1984) equation, assuming that covered interest rate parity ($f_t^h - s_t = i_{t,h} - i_{t,h}^*$) holds, where f_t^h is the forward exchange rate maturing in h periods ahead. Hence, assuming that the UIP conditions hold, the Fama equation can be written as:

$$\Delta s_{t+h} = \alpha + \beta (f_t^h - s_t) + u_{t+h}, \tag{3.3}$$

where $\alpha = 0$, $\beta = 1$ and $(f_t^h - s_t)$ is the forward premium: the difference between the forward and the spot exchange rate. The vast majority of studies estimating the above unrestricted equation have found that constant α is different from zero and slope coefficient β is significantly different from zero and actually very close to -1 (see, e.g. Bilson, 1981; Froot and Thaler, 1990; Bekaert and Hodrick, 1993). The opposite sign of β, which has become a stylised fact, is also referred to as the 'forward bias puzzle'. The fact that β is significantly different from zero implies that forward premiums contain enough predictive content for the depreciation rate, and this information can be extracted and exploited in an out-of-sample forecasting exercise.

A seminal work that exploits the predictive content of the forward premia is that of Clarida and Taylor (1997), which uses the spot rate and the forward exchange rates at different maturities as dependent variables in a linear vector error correction model (VECM), allowing for the *term structure of forward premia* to represent the long-run co-integrating vectors. What they find is that the term structure of forward premia not only have statistically significant in-sample predictive ability, but more importantly, exhibit out-of-sample predictability that outperforms the random walk in most of the cases considered. An extension of this work is that of Clarida et al. (2003), who examine improvements in the predictive performance of the above model by considering possible non-linearities using a Markov-switching VECM allowing for regime shifts only in the intercept and the variance-covariance matrix.[14] The empirical findings are quite promising since the non-linear specification is able to improve upon the linear VECM and the random walk, in both short and long horizons.

Nucci (2003) focuses on the forward premiums' predictive content as well, based on the evidence that there is a co-movement between the excess returns of cross-currency investments. He therefore investigates whether the forward premia of different currencies and maturities could have enough predictive content for the future spot FX rate of the home country. Although the in-sample evidence is empirically very supportive, the out-of-sample evidence does not seem positive since he finds predictability only for one out of three currencies using a VECM.

[14] Although the authors mention that regime shifts may be allowed for the parameters as well, they eventually used the specification described above.

Model 4. Purchasing power parity (PPP)

According to Dornbusch (1985), the strong or absolute version of the PPP model introduced by Cassel (1918), states that the price of a common and identical basket of goods in two countries should be the same at all times, adjusted for the exchange rate $\left(s_t = \frac{p_t}{p_t^*} \right)$ (law of one price). Whereas, the relative version of PPP states that the exchange rate should be equal to the relative price levels multiplied by a term that represents the trade obstacles $\left(s_t = \theta \frac{p_t}{p_t^*} \right)$. Hence, taking natural logarithms, the relative PPP model can be written as:

$$s_t = \alpha + \beta(p_t - p_t^*) + u_t \,, \tag{3.4}$$

where p_t is the logarithm of price levels, $\alpha = 0$, and $\beta = 1$. The empirical findings for this model are disappointing. Cheung et al. (2005) report that forecasts generated by this model are discouraging, especially for the short horizons (1 and 4 quarters ahead), while for much longer horizon (20 quarters), the forecasting performance of the model is improved since it outperforms the driftless random walk in most of the cases considered. Similar pessimistic results were obtained by Molodtsova and Papell (2009), who found predictability of the exchange rate for only one out of 12 countries for the 1-quarter-ahead horizon.[15]

Model 5. Monetary model

The monetary model, which is attributed to Frenkel (1976), Mussa (1976), and Bilson (1978), can be derived using the conventional real money demand as a function of output and interest rate. The money demand functions of the two countries are:

$$\text{Home: } m_t - p_t = a_1 y_t - a_2 i \;, \tag{3.5}$$

$$\text{Foreign: } m_t^* - p_t^* = a_1 y_t^* - a_2 i_t^* \;, \tag{3.6}$$

where m_t is the log of nominal money supply, y_t is the log of real output, and * denotes the foreign country. Also, the sign of α indicates the positive relationship between real

[15] Regarding Molodtsova and Papell (2009), the authors used the theoretical specification of the FX models developed by Mark (1995).

balances and real income, and the negative relationship with the interest rate. By subtracting the foreign demand function from that of the home country and bringing the money supply to the right-hand side, we get:

$$p_t - p_t^* = (m_t - m_t^*) - a_1(y_t - y_t^*) + a_2(i_t - i_t^*) \,. \qquad (3.7)$$

Assuming that the PPP holds at every point in time, we can derive the estimable monetary model by adding a constant term, a slope parameter for the relative money supply, and an error term. Hence, we have:

$$s_t = a + \beta(m_t - m_t^*) - \gamma(y_t - y_t^*) + \delta(i_t - i_t^*) + u_t \,. \qquad (3.8)$$

The positive sign of β means that with an increase in the money supply of the home country, the domestic demand for goods will increase, goods' prices will be pushed higher (demand-pull inflation), and, hence, the home currency will depreciate. The negative sign for the relative output implies that an increase in domestic income will increase the demand for money, which in turn will push the prices lower and, hence, cause a currency appreciation (see Frankel, 1984, p.240).

If we consider the presence of sticky price adjustment (where prices in the goods market adjust much slower than in the financial market), then the inflation rates (or price levels) can be entered into the monetary model as a predictor:

$$s_t = a + \beta(m_t - m_t^*) - \gamma(y_t - y_t^*) + \delta(i_t - i_t^*) + \eta(\pi_t - \pi_t^*) + u_t \,, \qquad (3.9)$$

where π_t is the inflation rate. This model implies that the PPP and UIP model hold at all time periods. We should note that some studies use the inflation differential as a predictor instead (Cheung et al. 2005), while others use the price levels (Engel and West, 2005). Empirical evidence for these models' out-of-sample predictability is negative. Meese and Rogoff (1983a, 1983b) find that random walk dominates both monetary models, while Cheung et al. (2005) find no predictability among the five currencies they examine, even at the 20-quarters-ahead horizon. Similar pessimistic results are reported by Chinn and Meese (1995), who find that neither model outperforms the naïve benchmark at the 1-month and 12-month horizons. Engel et al. (2008) use panel regressions for 18 currencies and find that the flexible model improves significantly upon the driftless RW in only five cases at the 1-quarter horizon, and in eleven out of 18 cases at 16-quarters ahead. Abhyankar et al.'s (2005) study also documents the failure of the flexible model fundamentals to predict out-of-sample the FX rate returns for both short and long horizons; whereas, under an asset-allocation framework, they provide empirical evidence for a significantly greater economic value of the FX rate forecasts generated from the monetary fundamentals than the value of the RW forecasts. An exception is the study of Chen and Mark (1996), which finds quite positive results, where a flexible monetary model predicts four out-of-sample exchange rate changes at the 3- and 4-year horizons.

Model 6. Taylor rule fundamentals

As mentioned before, Taylor rule predictors have been used the last decade for exchange rate forecasting purposes. As analytically described in the previous chapter, this rule was formulated by Taylor (1993) and describes how central banks set the short-term nominal interest rates as a function of the inflation, the deviation of the inflation from its target level, the output gap and the equilibrium real interest rate. Also, following Clarida et al. (1998) and Woodford (2003), we can assume that the nominal interest rate adjusts gradually to its target level, and again following Clarida et al. (1998) and also Molodtsova and Papell (2009), we can assume that monetary policy targets the real exchange rate, making the PPP hold at all times. Hence, by taking the difference between the two countries' policy rules and assuming that the UIP holds, we can derive similar specification to that used in Molodtsova et al. (2008, 2011) and Molodtsova and Papell (2009), and in the previous chapter:

$$\Delta s_{t+1} = \omega + a_{\pi}\pi_t - \alpha_{\pi}^{f}\pi_t{}^{f} + \beta_y y_t{}^{gap} - \beta_y^{f} y_t{}^{fgap} - \gamma_q^{f} q_t{}^{f} + \rho i_{t-1} - \rho^{f} i_{t-1}^{f} + u_{t+1}, \quad (3.10)$$

where π_t is the inflation rate, $y_t{}^{gap}$ is the output gap, $q_t{}^{f}$ is the real exchange rate of the foreign country, i_t is the short-term nominal interest rate and f denotes the foreign country. Molodtsova and Papell (2009) consider several specifications of the above model: i) a *symmetric* or *asymmetric* model, depending on whether each countries' rules include the same fundamentals or not; ii) a model with or without interest rate *smoothing*; iii) a *homogeneous* or *heterogeneous* model, where coefficients of inflation rates, output gaps and lagged interest rates are set equal or not. For our exchange rate forecasting race, we use a heterogeneous, asymmetric (including the real exchange rate of the home country) forecasting model, with interest rate smoothing and a constant, as in Wang and Wu (2012).

The out-of-sample empirical findings are in favour of this model, while most are highly sample-dependent. Molodtsova et al. (2008, 2011), Molodtsova and Papell (2009), and Inoue and Rossi (2012) are some of the studies that report the impressive forecasting performance of this model under different specifications; whereas Rogoff and Stavrakeva (2008) criticise the robustness of some of the aforementioned studies, focusing on the evaluation of the forecasts using different test statistics and different dates for the rolling regressions. Engel et al. (2008) use a calibrated Taylor rule forecasting model, and their results are not positive when the forecasts are compared with the naïve benchmark model.

Other exchange rate models

Several other empirical models have been used in the recent exchange rate literature. One model that has received little attention is that used by Sarantis (2006), which employs high-frequency data from the *financial markets* in a TVP-Bayesian VAR environment. The explanatory variables used as predictors are the depreciation rate, both short-term and long-term interest rate differentials, the equity return (stock's price growth) differential, and the exchange rate implied volatility. This model presents a significant forecasting performance that is able to outperform the naïve model at the 1-day-ahead horizon. This study also emphasises the importance of dealing with the parameters' instability, which cause complex non-linearities, as Sarantis (2006) finds larger forecasting errors when time-varying parameters are not used.

A study that exploits the empirical evidence that FX rates tend to follow a RW process is that of Carriero et al. (2009), which uses a *large panel of 33 bilateral nominal exchange rates*. The idea here is that, since macro fundamentals seem to sporadically contain the appropriate predictive content for the FX movements, a more a-theoretical approach based on the co-movement of the FX rates and their RW behaviour may be more helpful in an out-of-sample forecasting analysis. Hence, they use a Bayesian VAR model with a Minnesota prior, conducting a forecasting exercise based purely on time-series methods without any fundamental or theoretical background. Although their a-theoretical framework can be deemed a drawback in their analysis, they do present impressive forecasting results that are able to improve upon the naïve model for the majority of the FX rates considered, at both short and long horizons. The authors suggest that linear BVAR models should become a standard benchmark model in the literature, competing with other theory-based models. As we will see later, their conclusion is reinforced by our subsequent forecasting exercise.

Ferraro et al. (2015) present another interesting study, which investigates the predictive content of the *commodity prices of a country's major export*. They focus mainly on the Canadian/U.S. dollar nominal exchange rate returns and the oil prices. Their findings suggest a significant relation between the oil prices and FX changes on a daily frequency only, while results deteriorate when monthly and quarterly data are used. They also check the relation between the 1-period lagged oil commodity prices and FX movements and find that only when the parameter's time variation is taken into account is their model able to outperform the RW model at a daily frequency only. This is another study that emphasises the importance of time-variation as a necessary condition for generating good forecasts. More pessimistic results are reported by Chen et al. (2010), who also consider commodities' price predictability, including agricultural, mineral, livestock, and energy products (not oil prices), finding that prices are not able to forecast the FX rates out-of-sample, without being able to outperform the benchmark models in most of the cases. The in-sample evidence is more positive, as prices are found to Granger-cause the FX rate changes, but only when a TVP framework is allowed.[16]

Engel et al.'s (2015) study contributes to the forecasting literature with *factor models*; they obtain factors extracted solely from a panel of 17 FX rates. They construct a model using the (factor-FX rate) differential as a predictor and another specification, adding to the model the (macro fundamentals-FX rate) differential, with fundamentals coming from the Taylor rule, the monetary model, and the PPP model. The only specification that exhibit a predictive success in an out-of-sample analysis is that with the (factor-FX rate) differential plus the (PPP-FX rate) differential as predictors, at both short and long horizons. An in-sample study inspired by Engel et al. (2015) is that of Berg and Mark (2015), who examine the spill-over effects of a third country's macro

[16] The causality test used in Chen et al. (2010) is Rossi's (2005) test, which jointly tests the hypothesis of the in-sample predictive content of the predictors and the instability of parameters. Rossi (2005) underlines the drawback and limited power that the traditional Granger-causality test has when parameters' instability is detected.

factors on the nominal spot exchange rate. Their contribution rests on the fact that they construct factors from the Taylor rule (inflation, output gap, and interest rates), while their findings, after estimating their predictive models, suggest that these factors significantly enter into the model, driving the FX changes, and raising the regression's adjusted R^2.

Finally, the models that have been used increasingly in the last decade are the *micro-based* FX models, bridging the theoretical relation between exchange rate movements and currency order flows. The seminal paper of Evans and Lyons (2002) brought new insight into the FX forecasting literature by introducing a micro-based predictor, the order flows.[17] Their in-sample analysis, including a model with the interest rate differential and the order flows as regressors, reports significant positive coefficient for the order flow predictor with an R^2 of over 60%, while they make a first step in analysing the transmission mechanism of the order flows to the currency prices. Evans and Lyons (2005) build a forecasting model incorporating both aggregated and disaggregated order flows using a present-value framework, competing with traditional out-of-sample macro-based models (UIP with risk premium). The empirical results suggest the superior performance of the micro-based models especially at longer horizons. Based on this evidence, more studies took the next step. Rime et al. (2010) moved on to investigate the economic gains and value an investor may have when his asset allocation is based mainly on the order flows' information. Both in-sample and out-of-sample analysis led to the conclusion that order flows do have an impressive predictive content in forecasting FX rates using high-frequency data, in that models incorporating them deliver the highest economic gains (according to the Sharpe ratio) than other traditional FX models. Investors are even willing to switch from the random walk model strategy to an allocation strategy based on the order flow model forecasts.[18]

[17] As order flows, they define the difference between the buyer-initiated and seller-initiated orders for a foreign currency (Evans, 2010), or the sum over time of the signed interdealer trades (Evans and Lyons, 2002).

[18] It is worth mentioning that Evans (2010) revisits the exchange rate disconnect puzzle by arguing that microeconomic information such as foreign currency order flows can bridge the relation between spot FX rates and macro fundamentals such as GDP, prices and money supply. The researcher refers to a transmission mechanism where the currency trading between agents and dealers may transmit valuable information about the current macroeconomic developments and state to the dealer (who has limited information about the economy), then the dealer will update the quote of the spot FX rate accordingly. Finally, Evans (2010) conclude that dealers draw more information about the economy from the order flows than from the releases and announcements of the macro variables.

3.3 Linear and non-linear models

Structural changes, asymmetric information, weak rational expectations, instabilities, and non-linearities are the basic characteristics of the real world according to Sarantis (2006), and as presented in the previous chapter. According to Rossi's (2013b) critical survey, the predictive content of many macroeconomic variables has been found to be unstable over time, making the forecasting task less reliable. The most challenging issue is to identify the source of these instabilities and time-variations, and then choose the best model that will lead to reliable forecasts. She also mentions a list of studies, such as Rogoff and Stavrakeva (2008), Giacomini and Rossi (2010), Sarno and Valente (2009), Bacchetta and van Wincoop (2013), and others, which mention the relative predictive power of the macro fundamentals that appears to exist in an ephemeral manner.[19]

Hence, we employ several linear and non-linear models, each capturing different kinds of time-variation and instability, in an attempt to make significant inferences on which model generates more accurate out-of-sample forecasts and beats the benchmark driftless random walk model.[20] These models are the BVAR with the Minnesota prior (as used in the previous chapter; see Appendix B), the time-varying parameter BVAR with constant variance-covariance matrix, a heteroscedastic TVP-BVAR allowing both parameters and the variance-covariance matrix to change over time, and a dynamic model averaging and selection (DMA, DMS) models estimated with Bayesian methods.

Homoscedastic TVP- BVAR(p) model

The constant covariance matrix BVAR that allows for variation in the parameters has been presented analytically and used in the previous chapter. Although there are differences between them in the priors selection, we can recall the main characteristic

[19] Rossi (2013b) lists additional cases and topics other than the exchange rate literature where macro predictors' unstable predictive ability is documented. One of these is in finance, when one is trying to forecast the stock returns or when output growth predictability is examined (see, e.g. Goyal and Welch, 2003; Paye and Timmermann, 2006 and Giacomini and Rossi, 2006).

[20] Using a model similar to the TVP-VAR as a data-generation process, Canova (1993) shows that time-varying coefficients cause complex non-linearities and dependencies in the moments of the time-series. He also mentions that TVP-models encompassing these non-linearities are used in the literature to model the exchange rate data.

equations. Following Korobilis's (2013) notation, the reduced model can be compactly written in a SUR form as:

$$y_t = z_t \beta_t + \varepsilon_t \quad , \tag{3.11}$$

$$\beta_t = \beta_{t-1} + \eta_t \ , \tag{3.12}$$

where $z_t = I_m \otimes x_t = I_m \otimes (1, y_{t-1}, ..., y_{t-p})'$, $n = mk$ and $k = mp + 1$. Equation (3.12) is a driftless random walk state equation of the parameters, β_t is an $n\times 1$ state vector $[c_t', vec(B_{1,t}'), ..., vec(B_{p,t}')]'$ of the parameters, $\eta_t \sim N(0, Q)$ and $\varepsilon_t \sim N(0, \Sigma)$. It is assumed that η_t and ε_t are not correlated at all lags and leads. Regarding the priors, we follow the spirit of Primiceri (2005) and we use a training sample of size τ = 40 observations to calibrate the parameters' priors. A time-invariant parameter VAR(1) model is estimated with OLS and the estimates are used as initial conditions for the Kalman filter.

Priors, as in Koop and Korobilis (2009)

The priors for the parameters are obtained as described above:

$$\beta_0 \sim N(\beta_{OLS}, 4 \cdot V(\beta_{OLS})),$$

The priors for the covariance matrices Σ and Q are:

$$\Sigma \sim IW(\underline{S}^{\Sigma^{-1}}, \underline{V}^{\Sigma}) \quad \text{with} \quad \underline{S}^{\Sigma} = I_m \quad \text{and} \quad \underline{V}^{\Sigma} = m + 1.$$

$$Q \sim IW(\underline{S}^{Q^{-1}}, \underline{V}^{Q}) \quad \text{with} \quad \underline{S}^{Q} = 0.0001 \cdot \tau \cdot V(\beta_{OLS}) \quad \text{and} \quad \underline{V}^{Q} = \tau .$$

Posteriors

We estimate the parameters by sampling sequentially from the following conditional distributions:

a) Sample β_t conditional on the data using the Carter and Kohn (1994) algorithm along with the Kalman filter and the smoothing procedure. See Appendix B for more details.

b) Sampling Q^{-1} from the conditional density:

$$Q|\beta,\Sigma,z,y \sim IW(\overline{S}^{Q^{-1}},\overline{V}^{Q}),$$

where $\overline{S}^{Q^{-1}} = \left(\underline{S}^{Q} + \sum_{t=1}^{T}(\beta_t - \beta_{t-1})(\beta_t - \beta_{t-1})'\right)^{-1}$ and $\overline{V}^{Q} = t + \underline{V}^{Q}$.

c) Sampling Σ^{-1} from the conditional density:

$$\Sigma|\beta,Q,z,y \sim IW(\overline{S}^{\Sigma^{-1}},\overline{V}^{\Sigma}),$$

where $\overline{S}^{\Sigma^{-1}} = \left(\underline{S}^{\Sigma} + \sum_{t=1}^{T}(y_t - z_t\beta_t)(y_t - z_t\beta_t)'\right)^{-1}$ and $\overline{V}^{\Sigma} = t + m + 1$.

Heteroscedastic TVP- BVAR(p) model

This model assumes that both parameters and innovations are time-varying. The importance of possible non-linearities and instabilities, in the form of multivariate stochastic volatility, is discussed in D'Agostino et al. (2013), Primiceri (2005) and Koop and Korobilis (2009), underlying the fact that capturing shocks' heteroscedasticity may be proved crucial in generating good forecasts for the macroeconomic variables. Hence, we believe that this model may contribute in the exchange rate forecasting literature. We closely follow Primiceri's (2005) model. The reduced form model can be written as:

$$y_t = c_t + B_{1,t}y_{t-1} + B_{2,t}y_{t-2} + ... + B_{p,t}y_{t-p} + u_t, \tag{3.13}$$

where y_t is an $m\times 1$ vector of the observed variables, $B_{i,t}$ collects the parameters with $m\times m$ dimensions, and $u_t \sim N(0,\Omega_t)$ with the time-varying covariance matrix Ω_t. The covariance matrix can be decomposed as follows:

$$\mathrm{A}_t\Omega_t\mathrm{A}_t' = \Sigma_t\Sigma_t' \tag{3.14}$$

where A_t is the lower triangular matrix with 1 on its diagonal, summarising the relationships between the variables and Σ_t is the diagonal matrix with the standard deviations of the structural innovations as its elements. The aforementioned matrices are depicted below:

$$\mathrm{A}_t = \begin{bmatrix} 1 & 0 & . & . & 0 \\ \alpha_{21,t} & 1 & . & . & . \\ . & . & 1 & . & . \\ . & . & . & 1 & 0 \\ \alpha_{m1,t} & . & . & \alpha_{mm-1,t} & 1 \end{bmatrix}, \quad \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & . & . & 0 \\ 0 & \sigma_{2,t} & . & . & . \\ . & . & . & . & . \\ . & . & . & \sigma_{m-1,t} & 0 \\ 0 & . & . & 0 & \sigma_{m,t} \end{bmatrix}.$$

The above model can be rewritten as a linear and Gaussian state space representation, where the measurement equation is given by:

$$y_t = z_t\beta_t + \mathrm{A}_t^{-1}\Sigma_t\varepsilon_t\,. \tag{3.15}$$

Stacking all the parameters and intercepts in a vector; $B_t = \left[c_t, B_{1,t}, B_{2,t}, ..., B_{p,t}\right]$ and $\beta_t = vec(B_t)$, $z_t = I_m \otimes x_t = I_m \otimes \left(1, y_{t-1}, ..., y_{t-p}\right)'$ is an $m \times n$ matrix, $n = mk$ and $k = mp + 1$. The dynamics of the time varying parameters of the reduced form model, which represent the transition equations, follow driftless random walk processes as:

$$\beta_t = \beta_{t-1} + v_t\,, \tag{3.16}$$

$$a_t = a_{t-1} + \zeta_t\,, \tag{3.17}$$

$$\log\sigma_t = \log\sigma_{t-1} + \eta_t\,, \tag{3.18}$$

where eq. (3.18) follows a geometric random walk. Innovations are assumed to be distributed as multivariate normal and are independent of the parameters, such as:

$$V = \begin{bmatrix} \varepsilon_t \\ v_t \\ \zeta_t \\ \eta_t \end{bmatrix} \overset{iid}{\sim} N\left(0, \begin{matrix} I_m & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{matrix}\right). \tag{3.19}$$

Note that $E(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon = I_m$, $\otimes$ is the Kronecker product while matrix S is a block diagonal matrix, enhancing the independency of the parameters' evolution among the equations.

As regards the parameters' priors, we follow those proposed in Primiceri (2005) and Cogley and Sargent (2005), which seem to perform empirically well. Given that we have set our priors, the Gibbs sampler (MCMC algorithm) is used to simulate the conditional densities for $\beta^T, \mathrm{A}^T, \Sigma^T$ and V. A detailed description of the priors and the sequential sampling for the posterior inference can be found in Appendix B.

Bayesian Dynamic Model Averaging and Selection

The advantage of this model is not only that it allows for both coefficients and covariance matrices to change over time but that it also allows for the entire set of predictors to switch over time, depending on their relevance and importance. Bacchetta and van Wincoop (2004, 2013) present an empirical survey describing how currency market participants attribute more weight to the observed macro fundamentals that do not actually deserve it, than the true source of the FX fluctuations that might be unobserved. This is described as market 'confusion' across participants, especially in the short run, where an observed macro factor draws excessive attention, becomes the expected scapegoat, and, hence, causes chain reactions through the trading strategies. Such a practise was found empirically to shift across fundamentals and over time by Sarno and Valente (2009).

Structural breaks in macroeconomic variables, parameters' instability and uncertainty, changes in the monetary policy and consequences from the 'scapegoat theory' necessitate the use of a flexible econometric model that is able to pick the most relevant predictors, based on a posterior probability. The second feature of the DMA model is that it manages a large number of predictors and this allows us to use a wide range of them coming from all the exchange rate models that we have considered in this chapter as the theoretical drivers of the exchange rate changes, and examine which fundamental is more relevant to the FX future movements.[21]

We closely follow the DMA model developed by Raftery et al. (2010) and Koop and Korobilis (2012, 2013) in a heteroscedastic TVP-ARX specification. The state space model can be written as:[22]

$$y_t = z_t^{(k)}\theta_t^{(k)} + \varepsilon_t^{(k)}, \tag{3.20}$$

[21] Assuming that m predictors (including the intercept) are included in the DMA model, then 2^m forecasting models will be examined. When m is very large (more than 18 predictors), a forecasting exercise can be computationally demanding and sometimes infeasible.

[22] This TVP-ARX model (as in Ljung, 1987) allows for both lags of the dependent and exogenous variables to predict.

$$\theta_t^{(k)} = \theta_{t-1}^{(k)} + \eta_t^{(k)}, \tag{3.21}$$

where y_t is the log of exchange rate change, k = 1 ,….., K is the number of models, each using a different set of predictors, $z_t^{(k)}$ is a matrix of predictors that each of these k models uses, and $\theta_t^{(k)}$ collects the corresponding coefficients. Also, $\varepsilon_t^{(k)} \sim N(0, H_t^{(k)})$ and $\eta_t^{(k)} \sim N(0, Q_t^{(k)})$. Keeping Korobilis's (2012) notation, let $\Theta_t = (\theta_t^{(1)'}, ..., \theta_t^{(k)'})'$, $y_t = (y_t, ..., y_t)'$ and $L_t \in \{1, 2, ..., K\}$ indexing which individual model applies in each period. The DMA model is accompanied by a probability calculated in each time period, indicating which model should be used more (which predictors are more relevant) in the forecasting exercise. So, using this individual-model probability, DMA computes the weighted average of the *h*-period ahead forecasts across all models, while DMS will pick the individual model, with the corresponding relevant predictors, with the highest probability to forecast the exchange rate returns.[23] Hence, given the priors of the unobserved parameters (initial conditions of Kalman filter) and a prior model probability, the Bayesian inference can be easily achieved using the Kalman filter. The advantage of this model is that it uses some forgetting factors which allow us to avoid the usual MCMC simulation methods that would have been computationally unaffordable, by replacing the Kalman filter's components that require simulation. Another feature of the forgetting factors is that they control the weight assigned to the past observations and, hence, rule the evolution speed of the coefficients. When these factors are set equal to 1, then there is neither forgetting nor time-variation in our parameters and the DMA converges to a recursive but not dynamic Bayesian model averaging model.[24] More detail on the priors, posterior inference, model probabilities, forgetting factors, and forecasts can be found in the Appendix B.

<u>*New Keynesian DSGE model*</u>

New Keynesian DSGE models estimated with Bayesian likelihood methods have become a standard tool for the monetary policy authorities and other policy-making

[23] Wright (2008) describes the BMA model as a 'judicious pooling' of the predictive content from a whole set of numerous predictors to forecast the dependent variable.
[24] A standard BMA model was used by Wright (2008, 2009) for FX and inflation forecasting purposes. In both studies, the model exhibited sufficient forecasting performance outperforming the benchmark models in most of the cases in the short and long horizons.

institutions around the world for macroeconomic analysis, examining business cycle dynamics, and forecasting purposes (Smets and Wouters, 2007). Over the last decade, these models have been extended, embodying open-economy characteristics and allowing for more observables to enter into the model (such as the nominal exchange rates) as well as a richer set of disturbances. Nevertheless, the literature on exchange rate forecasting does not report any remarkable studies using DSGE models in an FX forecasting exercise.

The model that we use is an open-economy DSGE model for the U.S., closely following Gali and Monacelli (2005), Justiniano and Preston (2010), Steinbach et al. (2009), and Alpanda et al. (2011). In the goods market, monopolistically competitive firms set the prices, and households provide their labour services and set their wages. External habit formation in households' consumption, staggered prices and wages (Calvo, 1983), indexing wages (Rabanal and Rubio-Ramirez, 2005) and goods' prices (Smets and Wouters, 2002) to the previous period's inflation, are some of the model's features. The model also assumes that domestic retail firms import goods from abroad and sell them domestically, paying the exporters of the foreign country in terms of the home currency using the exchange rate. So far, the law of one price holds, but when the domestic retailer sets the imported products' price, he faces his own optimal mark-up problem and the price that he will charge may not be the same as the price he paid to the exporter. This will lead to incomplete exchange rate pass-through in the short term, while the deviations from the law of one price will be eliminated only in the very long term (Monacelli, 2005). To close the model, the UIP condition as in Adolfson et al. (2008) is used, which deals with several components of the country's risk premium and a Taylor rule with interest rate smoothing. The rich set of disturbances includes the home productivity shock, the consumption demand shock, cost-push shocks for both home and foreign country, the wage cost-push shock, the home country risk-premium shock, the monetary policy shock, and shocks for the foreign output, inflation, and interest rate.

The equations that characterise the equilibrium of the model are presented below, after the variables are log-linearised around their steady-state.[25] We closely follow the model from Steinbach et al. (2009) and Alpanda et al. (2011) where the home country

[25] The hat above each variable denotes the log-deviation of this variable from its steady-state value, while the bar denotes its steady-state. For instance, $\hat{y}_t = \log y_t - \log \bar{y}_t$.

is represented by the U.S. and the foreign country by the U.K. A detailed description of the model can be found in Appendix B.

Log-linearised model

The partially forward-looking New Keynesian IS curve is derived by log-linearising eq. (B.26) (see Appendix B):

$$\hat{c}_t = \frac{1}{1+\zeta} E_t \hat{c}_{t+1} + \frac{\zeta}{1+\zeta} \hat{c}_{t-1} - \frac{1-\zeta}{\sigma(1+\zeta)} (\hat{i}_t - E_t \hat{\pi}_{t+1}) + \mu_t^c, \tag{3.22}$$

where $\hat{c}_t$ is the domestic consumption, $\hat{\pi}_t$ is the inflation rate, ζ is the external habit formation coefficient, and σ is the risk aversion; μ_t^c is the consumption demand shock that follows an AR(1) process $\mu_t^c = \rho_c \mu_{t-1}^c + \varepsilon_t^c$ and $\varepsilon_t^c \sim i.i.d.\ N(0, \sigma_c^2)$, while $\hat{i}_t - E_t \hat{\pi}_{t+1}$ is the real interest rate. This equation links the current domestic consumption with the expected consumption and inflation and the one-period lagged consumption, while E_t denotes the expectations of a given variable formed at time *t*.

The equation that relates the domestic output with consumption comes from the goods market clearing condition and is given by log-linearising the goods market clearing condition:

$$\hat{y}_t = (1-\gamma)\hat{c}_t + \eta\gamma(2-\gamma)\hat{s}_t + \gamma \hat{y}_t^* + \eta\gamma\hat{\psi}_t, \tag{3.23}$$

where γ is the import share $(0 \le \gamma < 1)$, and η is the intertemporal elasticity of substitution between foreign and domestic products. In addition, $\hat{y}_t$ is the domestic output, * denotes the foreign county's variables, and foreign output is assumed to follow an AR(1) as $\hat{y}_t^* = \rho_{y*} \hat{y}_{t-1}^* + \varepsilon_t^{y*}$ and $\varepsilon_t^{y*} \sim i.i.d.\ N(0, \sigma_{y*}^2)$. Also, $\hat{s}_t$ is the terms of trade with $\hat{s}_t = \hat{p}_{f,t} - \hat{p}_{h,t}$ and $\hat{\psi}_t = \hat{e}_t + \hat{p}_t^* - \hat{p}_{f,t}$ denoting the deviation from the law of one price in the short-run, while $\hat{p}_t^*$ is the world price of the imported goods, $\hat{p}_{f,t}$ is the home currency price of imports, $\hat{p}_{h,t}$ is the price of domestically produced goods and $\hat{e}_t$ is the nominal exchange rate. Both equations can be derived by log-linearising equations (B.45a) and (B.39).

The partially forward-looking domestic inflation Phillips-curve is given by combining the log-linear version of equations (B.35) and (B.38):

$$\hat{\pi}_{h,t} = \frac{\beta}{1+\beta\phi_h} E_t \hat{\pi}_{h,t+1} + \frac{\phi_h}{1+\beta\phi_h} \hat{\pi}_{h,t-1} + \frac{(1-\theta_h)(1-\beta\theta_h)}{\theta_h(1-\beta\phi_h)} \hat{m}c_t + \mu_t^h , \qquad (3.24)$$

where $\hat{\pi}_{h,t}$ is the home goods price inflation, β is the discount factor, ϕ_h describes the degree to which prices are indexed to the previous period's price inflation, θ_h is the Calvo-type probability describing producers that do not adjust their prices, $\widehat{mc}_t$ is the firm's real marginal cost and defined as $\widehat{mc}_t = \hat{w}_t - \hat{z}_t + \gamma \hat{s}_t$ (derived after log-linearising eq. (B.32) in terms of labour productivity and terms of trade), where $\hat{w}_t$ is the real wage rate, $\hat{z}_t$ is the labour productivity that follows an AR(1) process as $\hat{z}_t = \rho_z \hat{z}_{t-1} + \varepsilon_t^z$ and $\varepsilon_t^z \sim i.i.d.\, N(0, \sigma_z^2)$.[26] The same AR(1) process is assumed for the cost-push shock μ_t^h. The U.K. economy is modelled as a closed-form version of the domestic economy. The foreign goods inflation is similar to the domestic producers Phillips curve:

$$\hat{\pi}_{f,t} = \frac{\beta}{1+\beta\phi_f} E_t \hat{\pi}_{h,t+1} + \frac{\phi_f}{1+\beta\phi_f} \hat{\pi}_{f,t-1} + \frac{(1-\theta_f)(1-\beta\theta_f)}{\theta_f(1-\beta\phi_f)} \hat{\psi}_t + \mu_t^f , \qquad (3.25)$$

where $\hat{\pi}_{f,t}$ is the domestic goods price inflation, ϕ_f has the same interpretation as ϕ_h, and μ_t^f is an exogenous cost-push shock following an AR(1) process, added in the Phillips curve (as in Justiniano and Preston, 2010, p.101), capturing the mark-up fluctuations. The wage-inflation Phillips-curve type equation is given by combining equations (B.27) and (B.28):

$$\hat{\pi}_{w,t} - \phi_w \hat{\pi}_{t-1} = \beta E_t \hat{\pi}_{w,t+1} - \phi_w \beta \hat{\pi}_t + \frac{(1-\theta_w)(1-\theta_w\beta)}{\theta_w(1+\theta\Xi)} (\hat{m}_t - \hat{w}_t) + \mu_t^w , \qquad (3.26)$$

where $\hat{\pi}_{w,t}$ is the nominal wage inflation and equal to $\hat{w}_t - \hat{w}_{t-1} + \hat{\pi}_t$, $\hat{\pi}_t$ is the weighted sum of prices for both domestically produced and foreign goods, defined as

[26] It should be noted that, by log-linearising equations (B.21) and (B.45a), it can be derived: $\hat{p}_t = \hat{p}_{h,t} = \gamma \hat{s}_t$.

$\hat{\pi}_t = (1-\gamma)\hat{\pi}_{h,t} + \gamma\hat{\pi}_{f,t}$. Also, ϕ_w describes the degree to which the nominal wage inflation is indexed to the price inflation, θ_w is the Calvo-type probability describing households that do not adjust their wage, θ is the inverse of labour supply elasticity, Ξ is the elasticity of substitution between households' labour services, $\hat{m}_t$ is the marginal rate of substitution which is defined as $\hat{m}_t = \sigma(\hat{c}_t - \zeta\hat{c}_{t-1})/(1-\zeta) + \theta(\hat{y}_t - \hat{z}_t)$ and μ_t^w is the exogenous mark-up shock that follows an AR(1) process as well. Three more characteristic equations need to be specified so we close the model, the UIP modified conditions, the real exchange rate and the monetary policy rule. The UIP as modified by Adolfson et al. (2008) is used, which takes into account the forward premium puzzle allowing for negative correlation between the expected depreciation rate and the risk premium. The log-linearised UIP is given by:

$$\hat{i}_t - \hat{i}_t^* = (1-\phi)E_t\hat{d}_{t+1} - \phi\hat{d}_t - \chi\hat{a}_t + \mu_t^d \qquad (3.27)$$

where $\hat{i}_t$ is the nominal interest rate, foreign interest rate $\hat{i}_t^*$ follows the univariate AR(1) process, $E_t\hat{d}_{t+1}$ is the expected depreciation rate, χ and ϕ are elasticity parameters, the nominal depreciation rate is defined as $\hat{d}_t = \hat{e}_t - \hat{e}_{t-1}$, a_t is the U.S. net foreign asset position defined as $\hat{a}_t = (1/\beta)\hat{a}_{t-1} + \hat{y}_t - \hat{c}_t - \gamma(\hat{s}_t + \hat{\psi}_t)$ (Schmitt-Grohe and Uribe, 2003), and the last component is the time-varying shock to the risk premium μ_t^d that follows the AR(1) process. The real exchange rate is defined as $\hat{q}_t = \hat{e}_t + \hat{p}_t^* - \hat{p}_t$, and if we time differentiate it, we can obtain $\hat{q}_t - \hat{q}_{t-1} = \hat{d}_t + \hat{\pi}_t^* - \hat{\pi}_t$, where $\hat{\pi}_t^*$ follows an AR(1) process. Also, an equation that relates the real exchange rate with the terms of trade and the deviation from the law of one price is given by $\hat{q}_t = (1-\gamma)\hat{s}_t + \hat{\psi}_t$. The last log-linearised equation is the Taylor rule that is given by:

$$\hat{i}_t = \rho\hat{i}_{t-1} + (1-\rho)(\lambda_\pi E\hat{\pi}_{t+1} + \lambda_y\Delta\hat{y}_t + \lambda_d\hat{d}_t) + \mu_t^i \qquad (3.28)$$

where ρ is the smoothing parameter, $\lambda_\pi, \lambda_y, \lambda_d$ are the relative weights of the expected inflation, real output, and depreciation rate, respectively, while μ_t^i is the monetary policy shock following an AR(1) process as well. The model's micro-foundation and estimation can be found in Appendix B.

3.4 Models, data, and forecasts

This section summarises the fundamental-based forecasting models, a description of the data used along with transformations suggested from the literature, and details for the forecasts' implementation and evaluation methods. The empirical results and relevant discussion will follow in the next section.

Exchange rate forecasting models

The corresponding Y_t vectors of dependent variables for the BVAR(p) and TVP-BVAR(p) models (both homoscedastic and heteroscedastic), include predictors from the major theoretical and empirical FX models presented in section 3.2:

UIP predictors: $Y_t = \left[\Delta s_t, i_t, i_t^*\right]'$, (3.29)

FPTS predictors: $Y_t = \left[\Delta s_t, \left(f_t^1 - s_t\right), \left(f_t^3 - s_t\right), \left(f_t^6 - s_t\right), \left(f_t^{12} - s_t\right)\right]'$, (3.30)

Taylor rule predictors: $Y_t = \left[\Delta s_t, y_t^{gap}, y_t^{gap*}, \pi_t, \pi_t^*, q_t, i_{t-1}, i_{t-1}^*\right]'$, (3.31)

where Δs_t is the nominal exchange depreciation rate, i_t is the nominal interest rate, $\left(f_t - s_t\right)$ is the forward exchange premium in different monthly maturities, y_t^{gap} is the output gap, π_t is the inflation rate, q_t is the real exchange rate and * denotes the figures of the foreign economy.

For the remaining fundamental-based models, we follow Mark (1995), Molodtsova and Papell (2009), Engel et al. (2008), Wang and Wu (2012) and Byrne et al. (2016), modelling the nominal exchange rate change as a function of its deviation from its fundamental-value:

$$\Delta s_{t+h} = a_t + \beta_t \left(\Omega_t - s_t\right) + u_{t+h} , \tag{3.32}$$

where Ω_t is the fundamental implied value.[27]

[27] One of the papers using this prediction model in a panel data framework is that of Engel et al. (2008), while Engel et al. (2015) use a similar model adding an extra term that describes the deviation of factors, generated from a cross-section of exchange rates, from the s_t.

Hence, for the remaining forecasting models the vector of predictors will contain both the fundamentals and the current nominal exchange rate:

PPP predictors: $Y_t = \left[\Delta s_t , p_t , p_t^* , s_t\right]'$, (3.33)

Monetary model (flexible) predictors: $Y_t = \left[\Delta s_t , y_t , y_t^* , m_t , m_t^* , i_t , i_t^* , s_t\right]'$, (3.34)

where p_t is the price level, y_t is the real GDP, and m_t denotes the money supply. We generate 20,000 draws and discard the first 5,000 for every parameter. We also thin the chain by keeping only the every tenth draw in order to mitigate the autocorrelation in the Markov chain. In the end, we obtain the mean of the marginal conditional posterior distribution as the point estimate.

Regarding the DMA and DMS models that follow a heteroscedastic TVP-ARX(*p*) specification, we opt to include a complete set of predictors coming from the major exchange rate models that we examined in the literature section. We therefore consider the following variables as predictors:

1. 1-month forward (USD/GBP) exchange rate premium
2. 3-month forward (USD/GBP) exchange rate premium
3. 6-month forward (USD/GBP) exchange rate premium
4. 12-month forward (USD/GBP) exchange rate premium
5. U.S. real GDP (seasonally adjusted)
6. U.K. real GDP (seasonally adjusted)
7. U.S. output gap (HP-filtered)
8. U.K. output gap (HP-filtered)
9. U.S. money supply (M1)
10. U.K. money supply (M4)
11. Real (USD/GBP) exchange rate
12. U.S. price inflation (annualised)
13. U.K. price inflation (annualised)
14. U.S. 10-year maturity government bond rates
15. U.K. 10-year maturity government bond rates

Regarding the DMA and DMS models, literature suggests making the data stationary, following Koop and Korobilis (2012, 2013) and Byrne et al. (forthcoming). More details will be given in the data section.

Regarding the DSGE model, we use the following 10 observed variables: the real output growth (Δy_t), the labour productivity growth (Δz_t), the nominal exchange rate depreciation rate (d_t), the consumer price inflation (π_t), the GDP deflator inflation

$(\pi_{h,t})$, the nominal wage inflation $(\pi_{w,t})$, the nominal interest rate (i_t), the foreign real output growth (Δy_t^*), the foreign GDP deflator inflation $(\pi_{h,t}^*)$, and the foreign nominal interest rate (i_t^*), as in Alpanda et al. (2011).

Data description

As mentioned earlier, we conduct a real-time forecasting study that is heavily based on data vintages that were available to the forecaster at the time the predictions were made, instead of fully revised data that most empirical studies use in the literature. As Clements (2012, 2015) and Clements and Galvao (2013) mention, a real-time forecasting exercise should mimic the conditions, environment and information set available to the forecaster at the time of making the predictions.

For the BVAR, TVP-BVAR, DMA and DMS models we use 18 quarterly macroeconomic variables (for both U.S. and U.K.) in total, spanning from 1979:Q1 to 2012:Q3. Starting with the vintage data, real GDP (seasonally adjusted) for the U.S. was extracted from the FED of Philadelphia real-time database, and the real GDP for the U.K. was extracted from the ONS. For both countries, the output gap is measured as *log* (*Actual real GDP*) – *log* (*Potential GDP*) while the potential output is obtained by applying the HP filter.[28] Regarding the price level and the inflation rate, we use the GDP deflator (seasonally adjusted) and we compute the inflation rate as the rate of inflation over the previous four quarters, $\pi_t = deflator_t - deflator_{t-4}$ (GDP deflators in natural logs). The price index for GDP was collected from the Federal Reserve Bank of Philadelphia for the U.S. and from the BoE for the U.K. For data that is not revised, we used the Pacific Exchange Rate Service website for the nominal USD/GBP exchange rate.[29]. The bilateral USD/GBP exchange rate is defined as the dollar price for a British pound. The USD/GBP forward exchange rates are from the BoE website.[30] We use M4 as a money supply proxy for the U.K. as in Chinn and Meese (1995) and Byrne et al. (2016), and M1 for the U.S. as in Chen and Mark (1996).[31] Regarding the variables'

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[28] Following Clausen and Meier (2005), we backcast and forecast our dataset by 12 quarterly datapoints, with an AR(4) model, in order to correct for the end-of-sample problem that filters like the HP present.
[29] The Pacific Exchange Rate Service's website can be found at: http://fx.sauder.ubc.ca/data.html.
[30] Forward rates have the following codes: XUDLDS1, XUDLDS3, XUDLDS6, XUDLDSY.
[31] We use revised data for the money stock since vintage data for this time-series is not available for the U.K.

transformation for the DMA-DMS models, a table with the respective transformations can be found in Appendix B, Table B.2.

Regarding the DSGE model, we use the CPI (seasonally adjusted) from the Fed of Philadelphia for the consumer price inflation, the employment cost index (ECI) as a proxy for nominal wages, and the output per hour index as a proxy for labour productivity.[32] Before we estimate the model, we demean the data since zero inflation, growth, and depreciation rate are assumed at the steady state, while the sample mean is added back to the generated forecasts before we evaluate them. All variables are transformed into natural logarithms, while interest rates are divided by 100.

Forecasts' implementation and evaluation

Our full sample runs from 1979:Q1 to 2012:Q3, while the out-of-sample period spans from 2006:Q3 to 2012:Q3. The number of lags (based on the BIC) for the VAR models has been set to 1, while we use a TVP-AR(2)X and 1 lag length for the exogenous predictors for the DMA-DMS models (as in Koop and Korobilis, 2012). We opt to run recursive estimations rather than rolling since regressions under the latter scheme have the potential gain of lessening the parameter instability effects over time (Cheung et al., 2005). Hence, a recursive estimation scheme will allow us to examine the predictive content of the fundamentals and the performance of our models, taking into account these time-variation effects. Regarding the generated forecasts for the VAR models, we use the same iterated forecasting formulas as in Chapter 2, following D'Agostino et al. (2013) and Korobilis (2013). Regarding the forecasts' evaluation, we use the relative RMSFE and the CW test of predictive ability as in Chapter 2, testing the null hypothesis that random walk and our forecasting model predict the same against the alternative that our model outperforms the benchmark RW model in predictive accuracy.

3.5 Empirical results and discussion

In this section, we present and discuss our results comparing them with the relevant literature. Firstly, we should refer to Rossi's (2013a) conclusions about the most

[32] I would like to thank Dr. Thomas Stark of the Federal Reserve Bank of Philadelphia for supplying the real-time data for the employment cost indexes.

successful predictors and econometric methods in the FX forecasting literature. What she characterises as a negative stylised fact is the relevant failure of the PPP and monetary fundamentals to predict the exchange rate movements at the short horizon, and the limited successfulness of the non-linear models. Also, the literature does not agree on whether UIP fundamentals predict well at short horizons and monetary predictors at long horizons. On the other hand, Taylor rule fundamentals present a significant predictive ability, especially at short horizon, while the BMA model seems to perform well in out-of-sample accuracy. In addition, we should not forget that comparing findings among different studies is not an easy task, since we have already mentioned that different empirical factors (data, choice of the predictors, econometric method, etc.) will definitely lead to different results (Rossi, 2013a). Hence, there is inherently a uniqueness in every forecasting study, and any 'bad' result (failure to outperform the benchmark random walk model) cannot entail the absence of contribution. Nevertheless, we can carefully discuss our results, given the difficulty mentioned in the literature to predict the FX rate changes, and find the points where we agree or not with the literature.

Table 3.1: Relative RMSFE of the BVAR(1) models vs. the RW model for h = 1-, 2- and 3-quarters ahead

	Δs_t	**FPTS**	**UIP**	**PPP**	**Monetary**	**Taylor rule**
	$t+1$	**0.991***	1.009	**0.950***	**0.985**	**0.965****
BVAR(1)	$t+2$	1.054	1.051	**0.986**	**0.995**	**0.990***
	$t+3$	1.016	1.032	**0.981**	**0.984****	**0.995**

Notes: This table shows the root mean square forecast errors using the FPTS, UIP, PPP, monetary and Taylor rule fundamentals as described in section 3.4. Values in **bold** denote the ratios that are below 1. Also, asterisks indicate the cases where the null hypothesis of equal predictive accuracy (one-sided CW test) is rejected against the alternative of outperforming the benchmark RW model at 1% (***), 5% (**), and 10% (*) significance levels.

The first results are shown in Table 3.1, with the forecasts generated from the linear BVAR(1) model. Overall, in ten out of 15 cases, our models outperform the benchmark driftless RW model, according to the relative RMSFE, which is less than 1 (in bold). Half of these results are confirmed by the CW test at least at a 10% significance level. More specifically, the UIP fundamentals seem to have not enough out-of-sample predictive power for the depreciation rate, especially for longer horizons. This is in line with Cheung et al. (2005) who find more positive evidence for the shorter horizons, while Clark and West (2006) and Molodtsova and Papell (2009) find no predictability of the USD/GBP depreciation rate for the 1-month-ahead horizon using linear regressions. The term structure of forward premia seem to be significantly (at the 10% level) good predictors, but only for the 1-quarter-ahead horizon. This is in contrast to the results of Clarida and Taylor (1997), whose VECM performs much better in longer horizons, using both the forward premia and the forward rates as predictors. The results are much more positive when PPP, monetary and Taylor rule fundamentals are used as predictors for both short and long horizons. Regarding the Taylor rule fundamentals, our findings are in line with the majority of the literature. Molodtsova and Papell (2009) use a similar theoretical model to ours, dominating the RW, while Engel et al. (2008) could not significantly predict the depreciation rate using a restricted asymmetric model with a constant, no interest rate smoothing, and homogeneous coefficients. Similar results are obtained using the monetary fundamentals, where we outperform the benchmark martingale difference model at all horizons, significantly only at the 3-quarter-ahead horizon. This finding is in contrast to the majority of the literature which confirms the poor predictability of the monetary fundamentals. Cheung et al. (2005) do not find any predictability at the short and very long horizons, Engel et al. (2008) find some predictability using an error-correction framework, while Molodtsova and Papell (2009) do not find any predictive content of the monetary fundamentals for the short-horizon. We end the linear analysis with the PPP fundamentals, where we outperform the naïve model at all horizons, but significantly only at 1-quarter-ahead horizon. Cheung et al. (2005) find predictability for the very long horizons only, Engel et al. (2008) for the 1- and 16-quarter-ahead horizons, but only when a drift is included in their PPP model, and Molodtsova and Papell (2009) fail to significantly generate better forecasts than the RW at the 1-month-ahead horizon.

Table 3.2: Relative RMSFE of the homoscedastic TVP- BVAR(1) models vs. the RW model for h = 1-, 2- and 3-quarters ahead

	Δs_t	FPTS	UIP	PPP	Monetary	Taylor rule
	$t+1$	**0.969**	1.015	1.029	1.191	1.036
Homoscedastic	$t+2$	1.044	1.059	1.191	3.374	3.406
TVP-BVAR(1)	$t+3$	1.023	1.049	1.128	4.338	6.523

Notes: See Table 3.1 notes for details.

Table 3.3: Relative RMSFE of the heteroscedastic TVP- BVAR(1) models vs. the RW model for h = 1-, 2- and 3-quarters ahead

	Δs_t	FPTS	UIP	PPP	Monetary	Taylor rule
	$t+1$	**0.986***	1.017	**0.967***	1.237	1.028
Heteroscedastic	$t+2$	1.076	1.076	1.006	1.461	1.232
TVP-BVAR(1)	$t+3$	1.097	1.044	**0.995**	1.234	1.037

Notes: See Table 3.1 notes for details.

Moving to the results generated from the TVP models, at a first glance, we can see the lack of forecasting improvement. Although we were expecting the TVP models to forecast better than the time-invariant ones due to the reasons mentioned earlier, the literature seems to support the opposite view. As Rossi (2013a) mentions, the empirical evidence for the TVP models' performance is mixed. They actually fit better in-sample than forecasting out-of-sample (see Terasvirta, 2006; Chin, 1991; Chinn and Meese, 1995). So, even if we are not surprised by the poor forecasting performance of the TVP exchange rate models, we believe that is a good opportunity to conduct this empirical analysis, expose their power, compare and discuss their results. According to our findings and the relative RMSFE metric, the only noteworthy case that displays a slight improvement compared to the linear BVAR are the FPTS fundamentals for the 1-quarter-ahead horizon, which generate better forecasts by 2.2% when the homoscedastic-TVP is used, and a 0.5% improvement when the heteroscedastic-TVP specification is used respectively. It is apparent that the non-linear models exhibit no forecasting improvement for any of the remaining cases (fundamentals), although the PPP predictors outperform the naïve model at the 1- and 3-quarter-ahead horizons when both parameters and the covariance matrix are allowed to evolve over time.

The poor forecasting ability of the proposed TVP models may be due to several reasons, which have been discussed in the literature, and some possible solutions have been proposed. The first reason is that TVP-BVAR models deal with many parameters with probably short sample periods (due to the fact that we sacrifice a sufficient sample to calibrate our data-based priors), which may lead to poor and imprecise in-sample parameter estimates (Koop and Korobilis, 2009). Another inherent drawback of this class of models is the fact that they use the same set of predictors in every time period until the sample exhausts, assuming that *all* the explanatory variables are more or less relevant for forecasting the FX changes. Also, the results in Table 3.2 indicate that, as the number of the explanatory variables increases (monetary and Taylor rule predictors), the predictive power of the model decreases, probably due to the in-sample overfit (Koop and Korobilis, 2012 and Clements et al., 2004).[33,34]

We therefore follow two potential solutions in this study. First, we conduct a sensitivity analysis in order to investigate the change of the TVP-models' out-of-sample performance by assuming non-informative normal priors $\beta_0 \sim \mathrm{N}(0,10^2)$ for the parameters instead of the data-based priors.[35] Details about the non-informative priors for the heteroscedastic TVP model can be found in the Appendix B. We believe that exposing models in different priors may be crucial and helpful for their performance. Doing so, we also 'release' the training sample that we used for the data-based priors' calibration and we include it in the estimation sample. The second solution is the usage of the DMA and DMS models, which take into account the relevance of explanatory variables' predictive content in each time period.

Sensitivity analysis

The results in Table 3.4 verify the improvement of the forecasting performance of the fundamentals-based models with respect to different priors. At first glance, the non-informative priors deliver better forecasts, especially for the PPP, monetary and Taylor rule models, outperforming the RW only at the short horizon (1-quarter ahead). So, although it is obvious that training sample priors deliver worse results, improving upon the benchmark model is still a difficult task since cases with a relative ratio below 1 for the homoscedastic TVP model number only 3 out of 15 (also verified by the CW test), compared to the 1 out of 15 cases using the informative priors.[36]

[33] Koop and Korobilis's (2012) work is a U.S. inflation forecasting study that documents the predictive failure of the TVP models to outperform the benchmark models, while the proposed DMA and DMS models were found to forecast out-of-sample much better at both short and long horizons.

[34] Clements et al.'s (2004) study is a critical survey comparing the linear with the non-linear forecasting models such as the Markov-switching and smooth-transition models from other studies. Their conclusion centres on the relative poor forecasting performance of the non-linear models and their inability to mimic the dynamics of the economy. They also argue that the parsimony and simplicity of the linear models may be proved sometimes more useful, while the large number of parameters and the in-sample overfitting are their main drawbacks.

[35] Regarding the prior for the homoscedastic TVP-BVAR(1) covariance matrix $Q \sim IW(\underline{S}^{Q^{-1}}, \underline{V}^{Q})$, where $\underline{S}^{Q} = 0.0001 * diag(\underline{V}_{\beta_0})$ and $\underline{V}^{Q} = (1+n)2$ as in Korobilis (2013), the prior for Σ and the posterior sampling remain the same.

[36] Byrne et al. (2016) use an econometric vehicle (homoscedastic TVP-BVAR) similar to ours to generate forecasts, inter alia, of the GBP/USD changes using the Taylor rule fundamentals, finding mixed evidence

Table 3.4: Relative RMSFE of the homoscedastic TVP- BVAR(1) models vs. the RW model for h = 1-, 2- and 3-quarters ahead

	Δs_t	FPTS	UIP	PPP	Monetary	Taylor rule
	t+1	1.045	1.073	**0.974***	**0.978***	**0.981****
Homoscedastic	*t+2*	1.155	1.178	1.009	1.074	1.011
TVP-BVAR(1)	*t+3*	1.453	1.124	1.186	2.172	1.091

Notes: These results are obtained using the non-informative priors. See Table 3.1 notes for details.

Table 3.5: Relative RMSFE of the heteroscedastic TVP- BVAR(1) models vs. the RW model for h = 1-, 2- and 3-quarters ahead

	Δs_t	FPTS	UIP	PPP	Monetary	Taylor rule
	t+1	1.015	1.026	**0.940****	**0.981****	**0.995***
Heteroscedastic	*t+2*	1.073	1.053	**0.963****	1.135	1.103
TVP-BVAR(1)	*t+3*	1.063	1.054	**0.994**	1.005	**0.993**

Notes: These results are obtained using the non-informative priors. See Table 3.1 notes for details.

Regarding the heteroscedastic TVP model, the difference in the results is more striking. First of all, the magnitude of the ratios has decreased a lot, indicating the forecasting improvement of the models, while the ratios below 1 have increased in six out of 15 cases. The PPP fundamentals' predictive content appears to be quite sufficient in forecasting the FX movements, significantly outperforming the RW at the 1- and 2-quarters-ahead horizons; the monetary model improves upon the benchmark only for the 1-quarter-ahead horizon; and the Taylor rule fundamentals are able to forecast well for the 1-quarter-ahead horizon (Table 3.5). Overall, the PPP, monetary and the Taylor rule fundamentals exhibit a substantial improvement, while the FPTS and the UIP predictors seem to predict slightly worse when switching to the non-informative priors.

The results from the Bayesian DMA and DMS models are mixed. Both models significantly beat the driftless random walk model, but only for the 1-quarter-ahead horizon; for the remaining horizons, forecasts are almost the same as the benchmark's forecasts (see Table 3.6). A similar model, without incorporating the time-variation in the parameters and innovations is used by Wright (2008) for FX movement forecasting

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of predictability, while the most successful monetary policy specification appears to be a homogeneous rule with interest rate smoothing targeting the real FX rate of the home country.

purposes. His results are mixed, finding significant predictability for the four bilateral FX rates that he examines except for the USD/GBP rate, using a set of 15 financial and macroeconomic predictors. His inability to significantly outperform the benchmark model may give some credit to the dynamic models that we use and the choice of our predictors, which appear to forecast well, especially at the short horizon.[37]

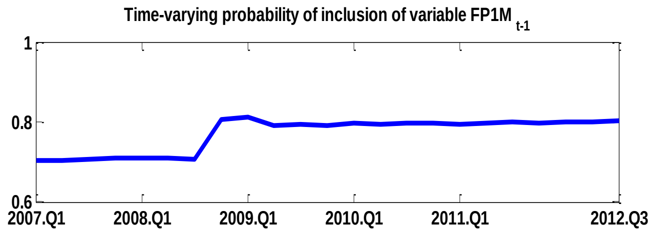
Table 3.6: Relative RMSFE of Bayesian DMA-DMS models vs. the RW model for h = 1-, 2- and 3-quarters ahead

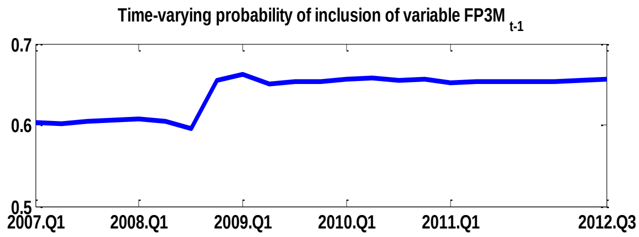
	Δs_t	15 Major Predictors		Δs_t	15 Major Predictors
	$t+1$	**0.970***		$t+1$	**0.979****
DMA	$t+2$	1.055	**DMS**	$t+2$	1.018
	$t+3$	1.062		$t+3$	1.042

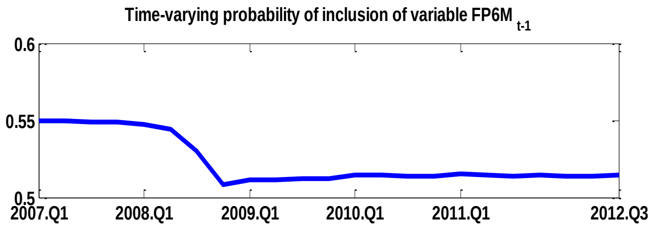
Notes: See Table 3.1 notes for details. Also, two lags of the dependent variable, one lag of the 15 theory-based predictors (as described in section 3.4) and an intercept, are used in both models.

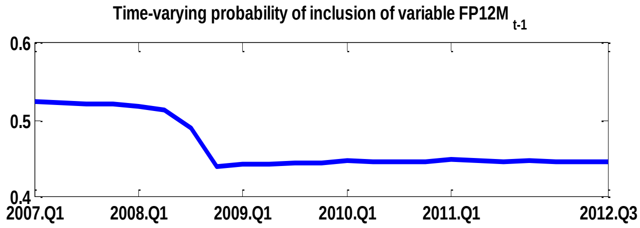
The probability (weight) that the DMA model assigns to each model (with the corresponding predictors) at each point in time is of great interest and importance. We therefore plot the time-varying posterior probabilities of inclusion of the predictors, indicating which predictor has the most relevant predictive content over the forecasting period. We focus on the 1-quarter-ahead horizon where we find significant predictability.

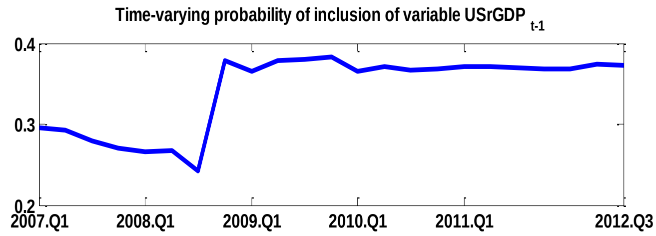
[37] Byrne et al. (forthcoming) examine the sources of the FX rate changes predictability uncertainty, by using BMA and BMS models incorporating parameters' time-variation, and they find predictability for most of the cases (assuming the U.S. as the foreign country) for horizons greater than one month. They also find that uncertainty lies in the estimation errors and the inability to capture the correct degree of coefficients' time-variation at the 1-month horizon.

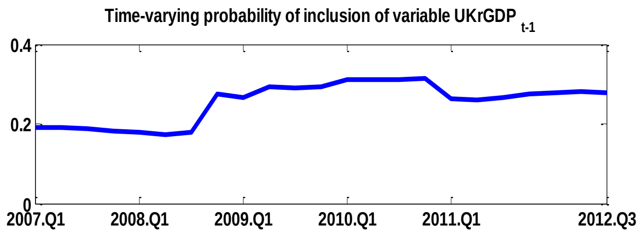

Time-varying probability of inclusion of variable FP1M t-1
1
0.8
0.6
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3

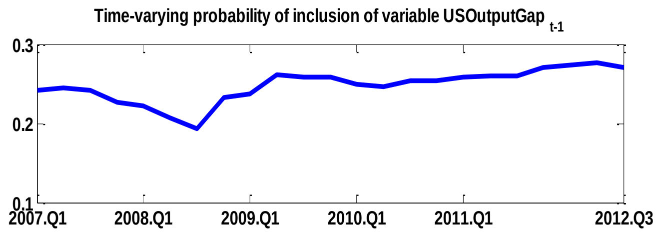

Time-varying probability of inclusion of variable FP3M t-1
0.7
0.6
0.5
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3

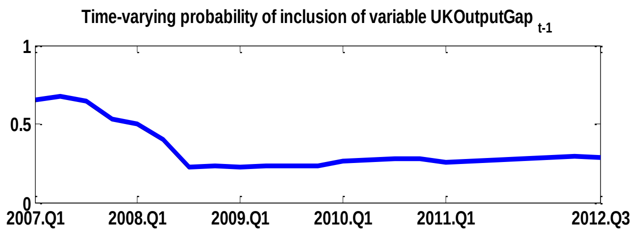

Time-varying probability of inclusion of variable FP6M t-1
0.6
0.55
0.5
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3

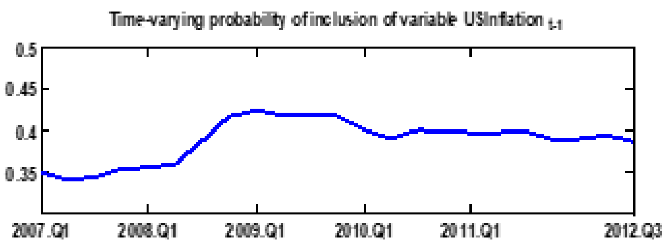

Time-varying probability of inclusion of variable FP12M t-1
0.6
0.5
0.4
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3

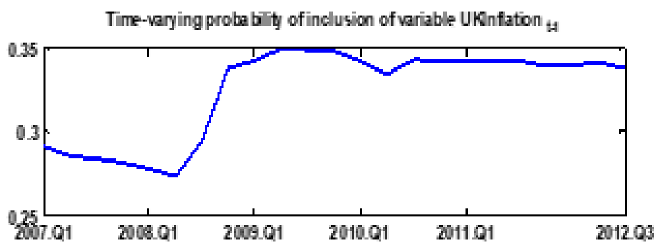

Time-varying probability of inclusion of variable USrGDP t-1
0.4
0.3
0.2
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3

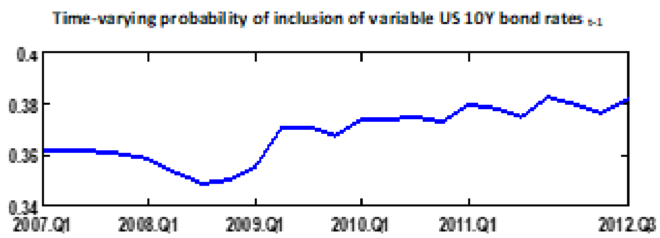

Time-varying probability of inclusion of variable UKrGDP t-1
0.4
0.2
0
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3

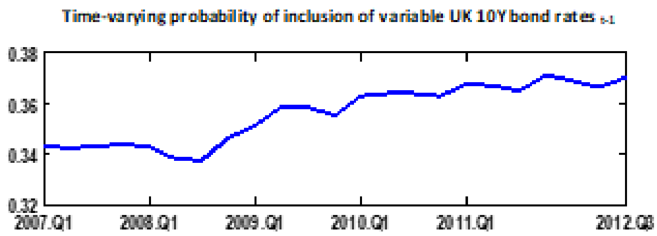

Time-varying probability of inclusion of variable USOutputGap t-1
0.3
0.2
0.1
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3


Time-varying probability of inclusion of variable UKOutputGap t-1
1
0.5
0
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3


Time-varying probability of inclusion of variable USInflation t-1
0.5
0.45
0.4
0.35
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3


Time-varying probability of inclusion of variable UKInflation t-1
0.35
0.3
0.25
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3


Time-varying probability of inclusion of variable US 10Y bond rates t-1
0.4
0.38
0.36
0.34
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3


Time-varying probability of inclusion of variable UK 10Y bond rates t-1
0.38
0.36
0.34
0.32
2007.Q1
2008.Q1
2009.Q1
2010.Q1
2011.Q1
2012.Q3

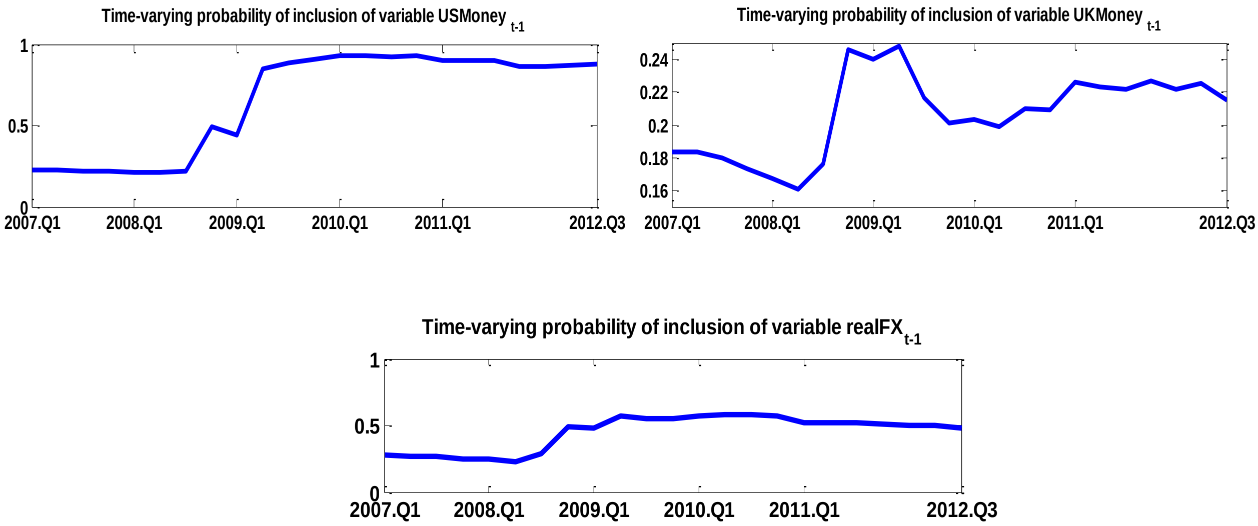


Figure 3.1 Time-varying posterior probability of inclusion of predictors for the 1-quarter-ahead horizon

It is obvious from the graphs that not all of the predictors are useful in forecasting since probabilities of inclusion above 0.5 throughout the forecasting sample are achieved for only five predictors. These are the forward premiums, especially the 1-month and 3-month forward premia, and the U.S. money stock, for which forecasting importance is extremely high for the period 2009:Q2–2012:Q3. Actually, the posterior probability of U.S. M1 began to rally in 2008:Q2 at the beginning of the financial crisis, when the U.S. Fed increased its bank reserves through large-scale asset purchases in 2009 (quantitative easing) and continuously decreased interest rates. The remaining predictors present no impressive predictive information, while probabilities do not appear to switch abruptly during that period.

As mentioned earlier, DSGE models have not been used extensively in the literature of exchange rate forecasting, and therefore we believe that exposure of such models would make this study more complete. According to our results, the structural model cannot outperform the naïve benchmark, although the forecasts generated are very similar to the RW model at the 2- and 3-quarter-ahead horizons. An analytical table with both prior and posterior densities can be found in Appendix Table B.1.

Table 3.7: Relative RMSFE of the DSGE model vs. the RW model for *h* = 1-, 2- and 3-quarters ahead

	Δs_t	
	t+1	1.282
DSGE	*t+2*	1.060
	t+3	1.034

Notes: See Table 3.1 notes for details.

To the best of our knowledge, Ca' Zorzi et al. (2017) and Alpanda et al. (2011) present some of the very few studies (if not the only ones), focusing on the nominal FX forecasting by setting-up rich DSGE. Both studies are based on similar theoretical frameworks and references (Justiniano and Preston, 2010; Gali and Monacelli, 2005), though their results are mixed, with those of Alpanda et al. (2011) being more positive at both short and long horizons.

3.6 Conclusions

We revisit the well-known Meese and Rogoff puzzle in an attempt to find a suitable econometric model and macroeconomic fundamentals with adequate predictive content and conditions under which we can forecast the nominal USD/GBP exchange rate changes and significantly outperform the driftless random walk model. We also focus on the highly topical issue of whether time-variation, as a special form of non-linearity, in both parameters and innovations can be crucial in the forecasting performance of our models.

The empirical evidence suggests that the two most successful models are the BVAR(1) model with the Minnesota prior and the heteroscedastic TVP-BVAR(1) model with the non-informative priors as described in the main text. The first finding lead us to mixed conclusions, meaning that we cannot safely infer the usefulness and the forecasting improvement of the models when time-variation is taken into account. Our findings can only join those of Clements et al. (2004) and Koop and Korobilis (2012), that forecasting with TVP models, or with non-linear models more generally, may sometimes lead to poor out-of-sample results, while their Achilles' heel seems to be the large number of states that these models deal with and the over-fitting problem that is caused (Geweke, Koop and Dijk, 2011)[38]. On the other hand, parsimonious specifications and linearity can prove more useful, leading to better forecasts. Also, the choice of priors for the TVP models has been proved of great importance, since the behaviour and the forecasting results of the models do change significantly and are improved when we switch from the training sample priors to non-informative priors. Regarding the choice of the fundamentals, the most successful variables in terms of out-of-sample predictive content are the price levels, since the PPP-based model beats the benchmark random walk model in most cases with better performance in the 1-quarter-ahead horizon. The next best predictors are the Taylor rule fundamentals and the monetary model predictors, especially at the short horizon. The 1-quarter-ahead horizon in our study proved the most predictable, when PPP, Taylor rule and monetary fundamentals are used, although the literature does not agree on the existence of predictability at this horizon when monetary predictors are used (Rossi, 2013a).

The results from the Bayesian DMA and DMS models are slightly different. Although the models agree on the 1-quarter-ahead predictability of the FX movements, they actually point to different fundamentals, in terms of predictive content, such as the 1- and 3-month forward premiums as well as the U.S. money stock, while results from the DSGE model are clearer, finding no predictability for the FX changes for any horizon. We should also mention the fact that forecasting particularly the nominal USD/GBP changes at both short and long horizons, has been proved by the literature to be one of the most difficult exercises among other bilateral exchange rates. Some characteristic papers are Chinn and Meese (1995), Chen and Mark (1996) and Engel, Mark and West (2008), which suggest that predictability for the nominal USD/GBP change cannot be achieved using the standard PPP, monetary and Taylor rule model fundamentals.

The empirical findings reported in this study denote the difficulty of outperforming the driftless random walk model in forecasting accuracy, and there is still progress to be made in convincingly resolving the Meese and Rogoff puzzle and bringing the nominal exchange rates closer to the macroeconomic variables. Nevertheless, the BVAR model with the Minnesota priors proved to be a very competitive model and we corroborate the view of Carriero et al. (2009) that this model should be established as a

[38] Geweke et al. (2011) suggest that a choice of parsimonious and thoughtful priors may help in overcoming the overfitting problem.

benchmark exchange rate forecasting model. Hence, we believe that the forecasting literature should choose an orientation to less sophisticated models exploiting the random walk behaviour of the nominal foreign exchange rates.

Chapter 4

Exchange Rates and Foreign Policy Crises. An In-sample and Out-of-sample Analysis

4.1 Introduction

For more than three decades, rare disaster models have attracted the attention and interest of many researchers. Most are motivated by the seminal empirical work of Rietz (1988), who extends the model of Mehra and Prescott (1985) and introduces a probability of extremely bad times in which consumption and equity returns drop dramatically, solving the puzzles of the high equity premium and low risk-free returns. Since then, many macro-finance and real business cycle models have been developed using probabilities of rare but extreme disaster events in an attempt to explain the major asset-pricing puzzles in international economics and finance. They focus on rare economic disasters that are followed by a sharp decrease in GDP per capita or consumption of more than 10% annually, due mainly to an economic event such as a financial crisis like the Great Depression, wartime destruction as in a world war, or a natural disaster like the Great Plague (Barro, 2006). After having gauged and incorporated the disaster and default probabilities of the economies, researchers explain the following puzzles: the high equity premium puzzle, the excess volatility of exchange rates and stock returns, the forward premium puzzle, and other empirical puzzles linking the exchange rates with options and stock markets, such as the zero correlation, on average, between a country's exchange rate returns and stock market returns (Barro, 2006; Gabaix, 2012; Farhi and Gabaix, 2016).

Motivated by the spirit of the literature on rare disaster models, we investigate the in-sample and out-of-sample predictive relationships between nominal exchange rate returns and foreign policy crises as these crises can directly influence and change the disaster risk of the economies over time (Berkman et al., 2011, 2015). First, we run in-sample predictive regressions, looking for the predictive impact of the foreign policy crises on the nominal USD/GBP returns once we introduce the crises variables in the macroeconomic fundamentals-based exchange rate models. The empirical work ends with a real-time out-of-sample forecasting exercise assessing the predictive power of the foreign policy crises predictors once they are combined with different macro fundamentals each time, while, at the same time, we try to outperform the benchmark random walk model without drift. By augmenting the traditional fundamentals-based models, we revisit the Meese-Rogoff disconnect puzzle by examining the usefulness and contribution of both macro fundamentals and foreign policy crises variables as predictors for the future path of the exchange rates.

We show that foreign policy crises have a predictive impact on the exchange rate returns under both frameworks. With regard to the in-sample findings, the augmented monetary-based and Taylor rule models, which incorporate the crises predictors, exhibit an increased explanatory power – as indicated by the adjusted R^2 – compared to the standard theoretical models, explaining how FX rate returns are influenced by the crises of different actor-states, severity, and violence. As for the out-of-sample results, the aforementioned models exhibit an improved forecasting power, especially at shorter horizons, outperforming the benchmark model according to the RMSFE metric and the CW test of predictive accuracy. In both analyses, the crises with the highest and most significant predictive power according to our results are the ongoing crises, and especially those that are non-violent. Finally, we find that once the PPP- and Fama-based models are combined with the crisis variables they do not deliver any striking improvement in our results.

Section 2 summarises the recently developed rare disaster model literature and its empirical findings. In Section 3, we describe in more detail the foreign policy crises database, as well as how we categorise our data according to violence and severity; we also present the descriptive statistics. Section 4 provides the in-sample and out-of-sample results of the predictive regressions and real-time forecasting exercise, respectively. Section 5 concludes this chapter with the final remarks.

4.2 Literature review

The major economic disasters of the 20th century that led to a fall in real GDP per capita of 15% or more, are considered by Barro (2006). He calibrates a model in the spirit of

Lucas (1978) and Mehra and Prescott (1985), incorporating a constant disaster probability (p), where an economy's output follows a random walk such as:

$$\log(\mathrm{A}_{t+1}) = \log(\mathrm{A}_t) + \gamma + u_{t+1} + v_{t+1} \quad . \tag{4.1}$$

Keeping Barro's notation, (A) is the output, $\gamma \geq 0$ is the drift representing the exogenous productivity growth, u_{t+1} is a zero mean normal *i.i.d.* shock, and v_{t+1} is a term picking up the rare but extreme disasters. In the case of a disaster, output will drop proportionately by a fraction $b \in (0,1]$, which is the size of the output sharp declining jump, and v_{t+1} will take the value of log(1-b) with a probability of p.[39,40] Barro's model solution and calibration lead him to tractable expressions and results explaining the high equity premium and the low risk-free rate puzzles. Since gauging the size distribution of macroeconomic disasters is a crucial factor for this kind of analysis, Barro and Ursua (2008) follow a peak-to-through method for tracking economic disasters and build histograms of all the events across countries characterised by a sharp decrease of real per capita consumption or GDP by more than 10% using a dataset with a long span (back to 1870) for 36 countries. This large sample and long-term history of the disaster events enables them to derive more accurate estimates for the disaster key parameters, finding a disaster probability of 3.5% annually, with a mean disaster size (b) of around 20% GDP shrinkage and 21% consumption shrinkage, and a mean duration of around three and a half years for both figures.[41]

Gabaix (2012), inspired by the empirical findings of Barro (2006), uses the time-varying probability and severity of the macro disasters, as well as linearity-generating processes for the inflation, stocks and bonds recovery rate from a potential disaster event –what he calls '*resilience*'- in order to derive closed-form and tractable

[39] In this kind of Lucas-type closed economy without government purchases and investment, output is equal to consumption.

[40] The probability p of a country experiencing a disaster is computed as the ratio between the number of disaster events and sample period.

[41] Although the disaster size b in the above studies is approximated by the mean of the corresponding sample-dependent observed histogram of the disaster macro events, Barro and Jin (2011) use a parametric approach specifying the distribution of b using the power-law probability density function of the form: $f(z) = \mathrm{A}z^{-(a+1)}$, where z = 1/(1-$b$) is the ratio of normal to disaster GDP, while this function is widely used not only in economics and finance. They show that a single power-law density is a good fit to the size distribution while a double power-law can provide an even better fit.

expressions for financial assets returns and prices.[42] After calibrating his model, he shows that numerous empirical asset-pricing puzzles can be understood and explained both qualitatively and quantitatively, such as the high stock prices volatility, the in-sample stock prices predictability using the price/dividend ratio as predictors, and bonds' upward sloping nominal yield curve. Farhi and Gabaix (2016) propose an improved model parsimoniously calibrated – inspired by the techniques used in Gabaix (2012) – introducing the exchange rates, contributing to resolving major puzzles of the exchange rate literature and their link with the option and stock market. Among others, they explain the forward discount puzzle, where the slope coefficient of the Fama regression is less than one and most of the time negative, and the zero correlation on average between the stock market returns and FX returns of two countries and between the stock market returns and risk reversals of two countries. Also, the fact that countries with high interest rates have high risk reversals, while higher risk reversals are linked with FX rate depreciation is also a fact matched with their model.

The disaster risk has also been used in the real business cycle literature, by authors such as Gourio (2012), who develops a closed-economy model incorporating a time-varying disaster risk and shows the very good fit of the asset return data and the negative impact of the disaster risk on the employment, investment, interest rates and stock prices, and a positive effect on the expected return on risky assets. Gourio et al. (2013) also use an RBC model of two countries with the same preferences and technology, employing a time-varying disaster risk due to a sharp decrease in productivity and capital destruction. Their results indicate a decrease in investment, employment, output, equity returns, risk-free rate and exchange rate appreciation in response to a disaster probability shock, while consumption slightly increases and then falls over time. Finally, their model can reproduce the negative estimate of the UIP slope coefficient and the high exchange rate volatility.

[42] Keeping Gabaix's (2012) notation the resilience is given by: $H_{it} = H_{i*} + \hat{H}_{it}$, where H denotes the resilience level, $\hat{H}_{it}$ is the variable part and H_{i*} is the constant component. The LG process applied to the resilience, yields the following expression: $\hat{H}_{it+1} = \frac{1+H_{i*}}{1+H_{it}} \exp(-\phi_{H_i}) \hat{H}_{it} + \varepsilon^{H}_{i,t+1}$, where ϕ_{H_i} is the speed of mean reversion and $\varepsilon^{H}_{i,t+1}$ is a zero mean error. This process actually approximates an AR(1) model since the $(1+H_{i*})/(1+H_{it})$ term moves around the value of 1 given that H_{i*} and H_{it} move together and very close to each other.

Another interesting and topical research area in international economics and finance that can be considered as a disaster is the currency market crash and the associated risk. A recent example is that of Brexit, whereby, after the referendum result was announced, sterling lost almost 10% of its strength against the US dollar in just one trading day. Other currency crises include Russia in 1998, Mexico in 1982 and 1994, and Argentina in 2002. Kaminsky (2006) examines historic currency crises using a sample of 20 countries for the period 1970–2002, identifying 96 crises in total. What is the probability of the occurrence of such a crash? Is the currency crash predictable? Which are the potential causes? How vulnerable to a crash is a country? These are some of the questions that the literature has focused on over the past three decades.

Frankel and Rose (1996) arbitrarily define the currency crash as a depreciation of at least 25% of the nominal exchange rate and 10% higher than the depreciation of the previous year. Eichengreen et al. (1996) enrich the definition by adding the effect of speculative attacks in the FX market. As a speculative pressure, they define the weighted average of exchange rate changes, interest rate changes and reserve changes, while a speculative attack (crisis) is a period in which this speculative pressure takes on extreme dimensions. They find that countries with relatively weak macro fundamentals are less able to defend their currency from a speculation attack. Also, Kräussl et al. (2016) state that currency crash risk can be measured either by using a function of the skewness and kurtosis of the FX rate returns distribution or the distribution of the FX rate option prices, while Brunnermeier et al. (2009) use the negative conditional skewness of the FX rate movements as a proxy for the crash risk that carry traders bear. Bekkour et al. (2015) examine the stability of the USD/EUR rate during the U.S. subprime crisis of 2007 and the E.U. sovereign debt crisis of 2009. More specifically, they use the moments of the risk-neutral distribution of the FX rate option prices (in terms of the implied volatilities) such as the variance, skewness and kurtosis as measures for the risk of future movements of the rate, the crash risk (expected direction of the FX rate) and the tail risk (low-probability of extreme events), respectively. Also, using the credit default spreads as a proxy for the sovereign debt risk of several E.U. countries, they find that changes in the creditworthiness of the member states have a direct impact on the FX rate returns and, more generally, on the stability of the euro currency. Finally, Farhi et al. (2015) use the currency option prices for estimating investors' compensations and excess returns during a carry trade. By regressing the exchange rate changes on the contemporaneous relative disaster risk exposure, they find a significant negative relationship indicating that, when the disaster risk of the home country increases, the home currency depreciates.

Following the spirit of Lizondo (1983), we develop a model, shown in Appendix C, describing the behaviour of the USD/GBP forward rate and its jumps, taking into account the potential regime switch that the Brexit decision may cause. This kind of model has been used to describe the so-called 'peso problem', whereby market agents have expectations about rare events but with great impact on the forward-looking asset prices (see, e.g. Lizondo, 1983; Lewis, 1991; Bekaert, Hodrick and Marshall, 2001).

It has been documented that gauging the disaster risk involves some difficulties, mainly due to the very low frequency of disaster events (e.g. in post-war periods) or even their absence in very small samples. This difficulty is compounded when we allow for this probability to vary over time and across countries (Barro and Ursua, 2012).[43] So, the literature suggests the following alternative techniques for estimating the time-varying risk, even for samples containing no major disasters. The first alternative comes from Bollerslev and Todorov (2011), who focus on how investors value and perceive the jump tail risk by using high-frequency intraday data for the short-maturity deep out-of-money S&P 500 option prices for the period 1996–2008. By looking for both negative and positive jumps of various sizes, they isolate and back out the disaster risk (jumps) of the S&P 500 price index finding that investors are actually more afraid of the negative jumps than the positive ones, as the left jump tail is more intense than the right.[44] A second approach that is mentioned in Barro and Ursua (2012) refers to the graph of the option-prices/strike price function, which looks like a 'smile'. The authors suggest that the shift of this function over time can be used as a proxy for the changes of the disaster risk.[45]

The last approach comes from Berkman et al. (2011), who use the number and severity of the foreign policy crises on an international level. They avoid estimating the disaster risk through the asset prices or consumption jumps since they argue that these

[43] Barro and Ursua (2012) provide a detailed survey of the major innovative studies on the rare macroeconomic disasters along with all the gauging techniques of the disaster risk and their main empirical findings.
[44] Backus et al. (2011) is another study using both consumption growth and the equity index option (with different strike prices), which deliver the true probability distribution and the risk-neutral density, respectively, focusing at the left tails.
[45] This 'smile' graph is also given by the currency option implied volatilities as a function of their strike prices (Farhi et al., 2015).

kinds of crises can directly influence and change the perceived disaster risk, and especially wars.[46] The advantage of this method is the adequately large number of documented crises around the world (447), along with the availability of the data spanning from 1918 to 2006, which enables them to overcome the short-sample constraints. Therefore, choosing foreign policy crises as a proxy for the time-varying disaster risk, they investigate the potential contemporaneous impact of these crises on the world stock market returns using a linear and a GARCH(1,1)-X specification, modelling the relation between stock market volatility and crises. Their findings are highly consistent with the behaviour of the rare disaster models, where the start of a crisis causes negative market returns and an increase to the returns volatility, a crisis termination causes positive returns reducing the returns volatility, and crises with higher severity and global 'attention' cause stronger reactions to market returns, while, more importantly, they show that the ongoing foreign policy crises significantly reduce the GDP growth of the next period (as measured by the Survey of Professional Forecasters). Berkman et al. (2015) extend the above work by looking for the predictive impact of foreign policy crises, expected stock market volatility, GDP growth forecasts, and other financial variables on the expected market risk premium.[47] Their findings suggest a significant positive impact from the crises on the market risk premium, consistent with the literature on rare disaster models.

4.3 Data structure and descriptive statistics

In this study, we follow the spirit of Berkman et al. (2011, 2015), using the number and severity of the foreign policy crises – henceforth FPCs – of the U.S. and the U.K. as a proxy for the change of the time-varying disaster risk. The actor-level dataset consisting of 470 FPCs (at the international level) and spanning from 1918 to 2013 is extracted from the International Crisis Behavior (ICB) database.[48] The definition of an

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[46] We should mention that Berkman et al. (2011) refer to the foreign policy crises on an international level as 'international political crises' due to the domestic political instabilities that a possible war may cause. Given that the latter term may confuse the reader, we stick to the term 'foreign policy crises', consistent with the crises literature (Brecher and Wilkenfeld, 1997).

[47] As expected market risk premium they define the expected stock market returns in excess of the 1-year Treasury bill rate.

[48] This open access database can be found at the following link: https://sites.duke.edu/icbdata/.

FPC is given by Brecher and Wilkenfeld (1997) as an event perceived as a threat to a country's basic values and followed by a finite time for response to the value threat with an increased probability of involvement in military hostilities. These three necessary conditions characterise a foreign policy crisis in this dataset, and all of them must be perceived by the decision-maker of the state-actor. For each crisis, the database provides 86 categorical variables for controlling, among others, the duration of the crisis (with specific dates), severity, crisis management and response techniques, violence level and the level of military involvement, giving the full identity and information needed. The online version also provides short summaries regarding the historical background and the progress of each crisis.

4.3.1 Crises and macro variables

Given that we focus on the USD/GBP returns, we separate our data into three major categories. In the first category, we collect all the U.S. foreign policy crises of any severity and violence either triggered or received by the U.S. In the second category, we collect all the U.K. foreign policy crises of any severity and violence either triggered or received by the U.K. The last category includes both U.S. and U.K. crises of any severity and violence either triggered or received by these two countries, along with U.S. involvement (military, financial, political and diplomatic) in third-party crises. The choice of the U.S. and the U.K. as crisis actors is reinforced by the fact that these two countries are involved in the majority of the FPCs included in this dataset, either individually or as participants in an alliance (such as NATO).

We should note that not all crises start with a conflict or end with a war, meaning that some crises are more severe than others, and market participants are expected to react according to their perceptions of the significance, participants' power and intensity of each crisis. Hence, we make a further distinction between the violent crises that may start with a violent act and/or continue as a serious clash with military involvement and potential casualties or involving a full-scale war, and the non-violent crises in which no serious violent actions have been employed either as a triggering cause or as a response. As mentioned earlier, the ICB database includes some control variables that help us to filter the crises accordingly. More specifically, as a *violent crisis*, we include:

a) FPC triggered by an indirect violent act (violent act to an ally country) or a direct violent act such as military invasion, airstrike, serious clash, large-scale military attack, border crossing or sea battle.
b) FPC where violent crisis management technique such as border clash, border crossing, airstrike, bombing high-value targets, or full-scale war have been used as a major response to the threat.

On the other hand, a *non-violent* crisis can be an economic threat, a verbal act, a violation of a treaty, a diplomatic incident, a declaration of war, a show of force, movement of forces or just a limited military threat.[49] We also consider the *total crisis*, which includes both violent and non-violent crises. We, therefore, use dummy variables to capture the different severities of each crisis, such as violent or non-violent, as described above. So, if a crisis belongs to the violent category, the corresponding dummy takes the value of 1, or 0 otherwise.

In the following graph, we plot the nominal USD/GBP rates with a summary of the major historic violent and some non-violent FPCs that took place over the period 1971–2013. For example, in 1976, we experienced a non-violent diplomatic incident between the U.K. and Iceland due to cod fishing with the presence of the Royal Navy in Icelandic waters assuring the safety and protection of the British fishers, hence, triggering an FPC for Iceland. During the sterling great devaluation in the first half of the 1980s, we have two violent crises, a full-scale war with many casualties in the Falkland Islands between the U.K. and Argentina, and the military invasion of the U.S. in Grenada. In January of 1991, the U.S. and an alliance of 28 states initiated "Operation Desert Storm", with the massive bombardment of Iraq resulting in the well-known Gulf War, which ended in April of same year. In early 1999, the Kosovo War between NATO (10 member states) and the Federal Republic of Yugoslavia (FRY) broke out as the latter failed to reach an agreement with the Kosovo Liberation Army (UCK). NATO began air attacks, triggering a crisis for the FRY, bombing military targets for around three months and causing civilian casualties, while ground clashes were never implemented. In 2001, the September 11 terrorist attack triggered a crisis for the U.S., and soon after the attack, the U.S. launched air and ground military operations against the Taliban regime in Afghanistan and the al-Qaeda network. After a new Afghanistan government was in

[49] Brecher and Wilkenfeld (1997) and ICB dataset's online notes provide an analytical description of each crisis control variable and definitions.

place, the crisis ended in December 2001 with the defeat of Taliban. In 2003, we observe the war against Hussein’s regime in Iraq due to the chemical weapons disarmament issue. In 2011, the Libyan civil war took place, with the military intervention of NATO.[50]

Foreign Policy Crises and USD/GBP exchange rate (1971-2013)

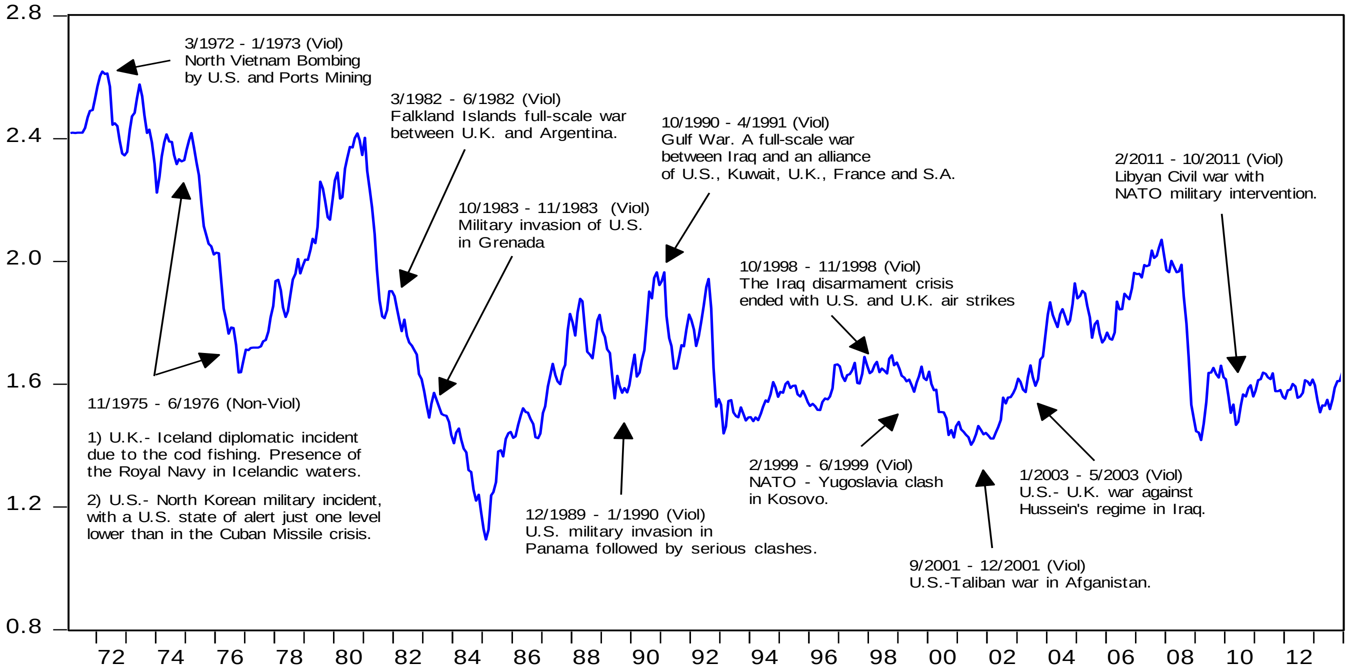


Figure 4.1: Graph plotting some of the major historic violent and non-violent FPCs, along with the nominal USD/GBP exchange rate over the period 1971–2013

Also, given that the start, progress and end of a crisis may produce different signals for the exchange rate market participants, we make a last distinction between the number of crises that start, end and are underway in each quarter, following the spirit of Berkman et al. (2011). The start date of a crisis is given by the date that the value threat is triggered, while the end date is given by the date that the decision-maker perceives the threat, time pressure and the likelihood of war declining and moving to normal conditions, as before the crisis. Most of the time, this date is taken from the decision-maker’s speeches, diaries or statements. The crisis that is underway in quarter *t* should not have a start or termination date during that quarter. By combining all of the above categories and distinctions, we end up with 27 crisis variables. For example, we

[50] These historic descriptions can be found in the online version of this database.

observe the number of U.S. violent foreign policy crises that start in each quarter, the number of U.K. non-violent FPCs which end in each quarter, the number of U.S.-U.K. with U.S involvement in third-party violent FPCs that are under way in each quarter, etc. Table 4.1 shows the descriptive statistics of all of our FPC variables, along with the stationarity results.

Table 4.1: Foreign Policy Crises descriptive statistics

Foreign Policy Crisis (FPC) variables		**Sum**	**Mean**	**Std. Dev.**	**DF-GLS**
U.S. Total	*Start*	61	0.35	0.68	-11.23***
	During	46	0.26	0.68	-4.94***
	End	61	0.35	0.79	-13.32***
U.S. Viol	*Start*	37	0.21	0.53	-12.03***
	During	10	0.06	0.23	-7.73***
	End	37	0.21	0.56	-13.42***
U.S. Non-Viol	*Start*	24	0.14	0.43	-11.84***
	During	36	0.20	0.63	-4.62***
	End	24	0.14	0.51	-13.27***
U.K. Total	*Start*	18	0.09	0.36	-11.88***
	During	16	0.10	0.34	-8.26***
	End	18	0.09	0.34	-13.54***
U.K. Viol	*Start*	10	0.06	0.23	-10.97***
	During	4	0.02	0.15	-10.29***
	End	10	0.06	0.26	-13.44***
U.K. Non-Viol	*Start*	8	0.05	0.30	-13.31***
	During	14	0.08	0.29	-7.10***
	End	8	0.05	0.34	-13.35***
U.S.-U.K. Total	*Start*	124	0.70	1.58	-6.22***
	During	131	0.74	1.67	-7.27***
	End	124	0.70	1.71	-12.87***
U.S.-U.K. Viol	*Start*	84	0.48	1.30	-4.92***
	During	76	0.43	1.23	-6.92***
	End	84	0.48	1.38	-12.96***
U.S-U.K. Non-Viol	*Start*	40	0.23	0.65	-12.79***
	During	55	0.31	0.90	-6.05***
	End	40	0.23	0.70	-12.56***

Notes: Table 4.1 reports the total number, mean, standard deviation and DF-GLS statistics of the FPCs of our dataset for the period 1971–2013. *Total* variable contains both *violent* and *non-violent* crises, as defined in the main text. The critical values of the DF-GLS test, with a null hypothesis of a unit root, are -2.57, -1.94 and -1.61 for the 1%(***), 5%(**) and 10%(*) significance levels, respectively.

With regard to the U.S., we observe 61 crises in total, 37 of which are violent, with the remaining 24 non-violent, while an average quarter has 0.35 crises. The probability of the U.S. entering (trigger or receive) into a violent FPC is 86% per year, and 55% per year into a non-violent one. Only 16 total crises have been documented for U.K., 10 of which are violent, with the remaining eight non-violent. Hence, we observe a lower sample probability of the U.K. entering into a violent FPC of around 23% per year, and 18% per year for entering into a non-violent crisis.[51]

4.4 Empirical results

4.4.1 In-sample results

To examine the predictive impact of the FPCs on the exchange rate returns, we add the FPC variables on the traditional FX models assuming homogeneous coefficients for countries' macroeconomic predictors. Consistent with the return prediction literature (see, e.g. Della Corte, Sarno and Tsiakas, 2009; Ferraro, Rogoff and Rossi, 2015), our predictive regression models take the following linear form:

$$\Delta s_t = c + a(Macro\ Fundamentds)_{t-1} + \beta Start_{t-1} + \gamma During_{t-1} + \delta End_{t-1} + \varepsilon_t, \quad (4.2)$$

where the nominal FX returns are regressed on the one-period lagged macroeconomic predictors and the Start, During and End variables of each crisis category. We employ macro predictors from the traditional FX fundamentals-based models such as the PPP-based model, the Fama-based model, the monetary-based model and the Taylor rule model, as described in the previous chapter. Hence, we have the following predictors:

Fama-based model: $(f - s)$

PPP-based model: $(p - p^*)$

Monetary-based model: $(y - y^*)$, $(m - m^*)$, $(i - i^*)$

Taylor rule model: $(y^{gap} - y^{gap*})$, $(\pi - \pi^*)$

where *p* is the price level, *f* is the three-month forward rate, *s* is the spot exchange rate, *y* is the real GDP, *m* is the money stock, *i* is the long-run interest rate, y^{gap} is the output gap, π is the inflation rate, * denotes the variables of the U.K., which represents the

[51] The probability of a country entering into a crisis is computed by the number of crises divided by the sample period (43 years).

foreign country, while the U.S. is the home country.[52] All of the above variables apart from the interest rates are in natural logarithms, while the interest rates are divided by 100. The DF-GLS test fails to reject the null of the unit root for the price, output gap, interest rate and money differential. Thus, we take the first difference of these predictors to ensure stationarity. The above model is estimated via OLS, while we use the heteroscedasticity and autocorrelation consistent covariance (HAC) estimator (Newey and West, 1987). The sample period spans from 1979:Q3–2012:Q3.

Tables 4.2, 4.3, 4.4 and 4.5 report the estimation results comparing the regressions of the ‘augmented’ models (including the FPCs as predictors) with the standard theory-based ones. We use the adjusted-R^2 for assessing whether or not the explanatory power of each model increases. Adjusted-R^2 is the most appropriate measure for this assessment since it adjusts for the different number of predictors included in the model. The in-sample results for the PPP-based and Fama-based models are mixed. Although forward premium predictors are always negative and significant at least at the 10% level, we have only four augmented Fama-based models with adjusted-R^2 higher than that of the standard Fama-based model.[53] The cases that stand out are when the U.S. and U.K. non-violent FPCs are used as predictors with a positive effect for crises that start or are under way, and a negative effect for crises that end in each quarter. Somewhat similar results are obtained when PPP-fundamentals are used as regressors. The price differentials are significantly negative, while, again, when the U.S. and U.K. non-violent FPCs are included, the predictive power of the augmented models increases slightly.

[52] We use the GDP deflator as a proxy for the price level and inflation, M1 is used for the money stock of the U.S. and M4 for the U.K., the 10-year Treasury bond rate is the proxy for the interest rate, while HP-filter is used to extract the potential output.
[53] The significantly negative parameter of the forward premium is in line with the literature (see, e.g. Bilson, 1981; Froot and Thaler, 1990; Bekaert and Hodrick, 1993).

Table 4.2: Fama-based models' OLS results

Fama-based models	*constant*	*(f-s)*	*Start*	*During*	*End*	*adj. R^2*
w/o FPCs	-0.0088	**-1.6420***				0.062
US Total	**-0.0160****	**-1.8195****	0.0082	**0.0098****	0.0024	**0.075**
US Viol	-0.0086	**-1.6863***	-0.0048	-0.0007	0.0035	0.041
US Non-Viol	**-0.0159****	**-2.0119****	**0.0192****	**0.0110*****	0.0016	**0.093**
UK Total	**-0.0105***	**-1.6503***	0.0016	**0.0168***	-0.0011	0.051
UK Viol	-0.0076	**-1.6815***	-0.0163	-0.0293	0.0078	0.051
UK Non-Viol	**-0.0114****	**-1.7069***	0.0421	**0.0256*****	**-0.0208***	**0.076**
US_UK Total	-0.0079	**-1.7551***	-0.0027	-0.0010	**0.0023***	0.054
US_UK Viol	-0.0063	**-1.8553****	-0.0038	-0.0048	0.0025	**0.071**
US_UK Non-Viol	**-0.0112***	**-1.6591***	-0.0019	0.0053	0.0041	0.055

Notes: Table 4.2 reports the OLS regression results of the predictive models with and without including the FPC predictors. Estimates in **bold** denote significance at the 1%(***), 5%(**) and 10%(*) levels, based on HAC (Newey and West, 1987) standard errors. Adjusted R^2 in **bold** indicates the models with an in-sample predictive power higher than the standard theoretical model of the first row, which does not contain any FPC predictor. The sample period spans from 1979:Q3–2012:Q3.

Table 4.3: PPP-based models' OLS results

PPP-based models	*constant*	$\Delta(p\text{-}p^*)$	*Start*	*During*	*End*	*adj. R^2*
w/o FPCs	-0.0043	**-0.8156***				0.039
US Total	-0.0095	**-0.8500***	0.0071	**0.0082***	0.0013	**0.042**
US Viol	-0.0035	**-0.9899***	-0.0037	-0.0100	0.0022	0.021
US Non-Viol	**-0.0093***	**-0.9809****	**0.0163***	**0.0101****	-0.0004	**0.058**
UK Total	**-0.0057***	**-0.7495***	-0.0116	0.0136	0.0112	-0.007
UK Viol	-0.0027	**-0.7256***	-0.0272	**-0.0359***	0.0153	0.006
UK Non-Viol	-0.0073	**-1.0336****	**0.0404***	**0.0284*****	-0.0166	**0.058**
US_UK Total	-0.0027	-0.8158	-0.0026	-0.0020	**0.0032****	0.019
US_UK Viol	-0.0017	**-0.9090***	-0.0034	-0.0039	0.0025	**0.042**
US_UK Non-Viol	-0.0073	-0.8336	-0.0013	0.0036	**0.0091****	0.011

Notes: See Table 4.2 notes for details.

The in-sample results from the monetary-based and Taylor-rule models are more positive, stressing the predictive impact of the FPC variables. With regard to the monetary models, output and money differentials have significantly positive and negative effects on the FX rate change, respectively. We find seven cases in which the augmented models exhibit higher power, while the ongoing FPCs have a significant positive effect, causing the U.S. dollar to depreciate against the British pound. As for the Taylor rule models, we find eight augmented models with higher adjusted-R^2. More specifically, we find highly significant positive estimates for the output gap differential and negative estimates for the inflation differential, while the sign for the ongoing crises is not the same among the models.

Table 4.4: Monetary-based models' OLS results

Monetary-based models	*constant*	$(y\text{-}y^*)$	$\Delta(i\text{-}i^*)$	$\Delta(m\text{-}m^*)$	*Start*	*During*	*End*	*adj.* R^2
w/o FPCs	**-0.3654*****	**0.1173*****	0.7729	**-0.1969****				0.085
US Total	**-0.4291*****	**0.1362*****	0.7261	**-0.1849*****	0.0022	**0.0123*****	0.0026	**0.093**
US Viol	**-0.3970*****	**0.1275*****	0.6494	**-0.2161*****	-0.0113	0.0188	0.0042	0.079
US Non-Viol	**-0.3492*****	**0.1103*****	1.0037	**-0.2054*****	0.0102	**0.0119*****	0.0024	**0.145**
UK Total	**-0.4056*****	**0.1294*****	0.8036	**-0.2005*****	-0.0085	**0.0228***	0.0129	0.085
UK Viol	**-0.3094*****	**0.0992*****	0.9410	**-0.2214*****	-0.0139	-0.0066	0.0057	**0.108**
UK Non-Viol	**-0.3695*****	**0.1173*****	1.0779	**-0.1993*****	0.0386	**0.0345*****	0.0011	**0.153**
US_UK Total	**-0.3201*****	**0.1016*****	0.8944	**-0.2482*****	-0.0019	0.0014	**0.0031****	**0.121**
US_UK Viol	**-0.3103*****	**0.0997*****	0.9144	**-0.2172****	-0.0029	-0.0023	0.0025	**0.120**
US_UK Non-Viol	**-0.3720*****	**0.1177*****	0.9871	**-0.2339*****	-0.0023	**0.0084****	**0.0081***	**0.145**

Notes: See Table 4.2 notes for details.

Table 4.5: Taylor-rule models' OLS results

Taylor-rule model	*constant*	$\Delta(y^{gap}\text{-}y^{gap*})$	$(\pi\text{-}\pi^*)$	*Start*	*During*	*End*	*adj.* R^2
w/o FPCs	-0.0103	**0.5871****	**-0.7930***				0.175
US Total	**-0.0169***	**0.5432****	**-0.7457****	0.0028	**0.0143****	0.0044	**0.189**
US Viol	-0.0095	**0.5691****	**-0.8038****	-0.0049	-0.0007	0.0000	0.168
US Non-Viol	**-0.0192****	**0.5457*****	**-0.8703*****	**0.0145***	**0.0195*****	0.0062	**0.211**
UK Total	**-0.0141***	**0.4789****	**-0.7709****	-0.0003	0.0276	0.0118	**0.177**
UK Viol	-0.0087	**0.6151*****	**-0.8180****	-0.0103	**-0.0486****	-0.0007	**0.182**
UK Non-Viol	**-0.0191*****	**0.5127*****	**-0.9408*****	0.0336	**0.0694*****	**0.0471*****	**0.223**
US_UK Total	-0.0083	**0.5804****	**-0.7653****	-0.0007	-0.0024	0.0016	**0.178**
US_UK Viol	-0.0052	**0.5822*****	**-0.7880****	-0.0024	**-0.0074****	0.0001	**0.192**
US_UK Non-Viol	**-0.0155***	**0.4909****	**-0.7597****	0.0014	0.0079	**0.0092*****	**0.188**

Notes: See Table 4.2 notes for details.

As a final remark of the in-sample analysis, we should note that the U.S. non-violent crises and U.K. non-violent crises are able to deliver results with the highest predictive power, while the ongoing FPCs seem significantly to affect more often the FX rate movements than the Start and End regressors. In addition, the ongoing FPCs tend to depreciate the home currency (US dollar), which is consistent with the disaster literature (Farhi and Gabaix, 2016).

4.4.2 Out-of-sample results

The finding that, in some cases, foreign policy crises can explain in-sample the changes in the spot rates does not guarantee their ability to forecast them in an out-of-sample framework. To examine this case, we switch to a real-time forecasting exercise using both FPC and macroeconomic variables as predictors in an attempt to outperform the driftless random walk model.[54] Conclusions from the previous chapter suggest the usefulness of the linear Bayesian VAR model as an econometric vehicle for forecasting the future path of FX returns and, hence, we choose this kind of model for this study as well. We employ the reduced-form BVAR specification as in Korobilis (2013), using the Minnesota prior, and we generate iterated forecasts for the nominal USD/GBP returns for 1 up to 4 quarters ahead using a recursive scheme, as in the previous chapter. We employ the abovementioned fundamentals-based models incorporating the FPC predictors. To be more specific, for each fundamentals-based model, we use four different specifications. In the first, we include only the FX returns and macro fundamentals (standard model), while in the rest we try to exploit the impact that different points of the crisis course may have on the returns. Hence, the vectors of the dependent variables are given as follows:

Fama model: $Y = \left[\Delta s_t, (f_t - s_t)\right]'$,

$$Y = \left[\Delta s_t, (f_t - s_t), US\_Start_t, UK\_Start_t, US\_UK\_Start_t\right]',$$
$$Y = \left[\Delta s_t, (f_t - s_t), US\_During_t, UK\_During_t, US\_UK\_During_t\right]' \text{ and}$$
$$Y = \left[\Delta s_t, (f_t - s_t), US\_End_t, UK\_End_t, US\_UK\_End_t\right]'.$$

PPP-based model: $Y = \left[\Delta s_t, (p_t - p_t^*)\right]'$,

$$Y = \left[\Delta s_t, (p_t - p_t^*), US\_Start_t, UK\_Start_t, US\_UK\_Start_t\right]',$$
$$Y = \left[\Delta s_t, (p_t - p_t^*), US\_During_t, UK\_During_t, US\_UK\_During_t\right]' \text{ and}$$
$$Y = \left[\Delta s_t, (p_t - p_t^*), US\_End_t, UK\_End_t, US\_UK\_End_t\right]'.$$

Monetary model: $Y = \left[\Delta s_t, (y_t - y_t^*), (m_t - m_t^*), (i_t - i_t^*)\right]'$,

$$Y = \left[\Delta s_t, (y_t - y_t^*), (m_t - m_t^*), (i_t - i_t^*), US\_Start_t, UK\_Start_t, US\_UK\_Start_t\right]',$$

[54] We use vintage data for all our macro variables except interest rates, exchange rates and money stock.

$$Y = \left[\Delta s_t, (y_t - y_t^*), (m_t - m_t^*), (i_t - i_t^*), US\_During_t, UK\_During_t, US\_UK\_During_t\right]' \text{ and}$$
$$Y = \left[\Delta s_t, (y_t - y_t^*), (m_t - m_t^*), (i_t - i_t^*), US\_End_t, UK\_End_t, US\_UK\_End_t\right]'.$$

Taylor rule model: $Y = \left[\Delta s_t, (y_t^{gap} - y_t^{gap*}), (\pi_t - \pi_t^*)\right]'$,

$$Y = \left[\Delta s_t, (y_t^{gap} - y_t^{gap*}), (\pi_t - \pi_t^*), US\_Start_t, UK\_Start_t, US\_UK\_Start_t\right]',$$
$$Y = \left[\Delta s_t, (y_t^{gap} - y_t^{gap*}), (\pi_t - \pi_t^*), US\_During_t, UK\_During_t, US\_UK\_During_t\right]' \text{ and}$$
$$Y = \left[\Delta s_t, (y_t^{gap} - y_t^{gap*}), (\pi_t - \pi_t^*), US\_End_t, UK\_End_t, US\_UK\_End_t\right]'$$

We should note that the *Start*, *During* and *End* variables refer to the Total crises, which include both violent and non-violent FPCs, as described in the main text. The precision of the mean forecasts over the whole out-of-sample period (2006:Q1–2012:Q3) is evaluated using the RMSFE as a standard metric, while the driftless random walk is our benchmark model. We also use the one-sided Clark and West (2007) test for the significance of our results.

Table 4.6 shows the relative RMSFE between our models and the benchmark model. The out-of-sample results from the PPP and Fama models are not very positive. Both standard and augmented models do not significantly outperform the benchmark model at any horizon. As in the in-sample analysis, the results from the monetary and Taylor rule models are more optimistic. With regard to the monetary model, the inclusion of the FPCs that are underway in each quarter not only significantly outperforms the benchmark model but also improves the RMSFE by 3% and 5.2% compared to the standard monetary model (second column), for the 1- and 2-quarter horizons respectively. These results are of more interest given that the standard monetary model is not able to significantly outperform the random walk at any horizon. Finally, the results from the Taylor rule models are similarly interesting due to the forecasting power that the ongoing FPCs provide for the 1- and 2-quarter ahead horizons, where the RMSFE is improved by 2.2% and 3.3%, respectively. In terms of relative RMSFE, we see that FPCs that start or end in each quarter do not seem to offer any improvement in the results.

Table 4.6: Fundamentals-based out-of-sample results

Fama-based models	*w/o FPCs*	*Start*	*During*	*End*
t+1	1.015	1.014	1.023	1.010
t+2	1.044	1.040	1.046	1.044
t+3	1.027	1.027	1.041	1.030
t+4	**0.996**	**0.997**	1.046	**0.999**
PPP-based model				
t+1	1.000	1.000	1.020	**0.997**
t+2	1.026	1.022	1.041	1.027
t+3	1.012	1.015	1.039	1.014
t+4	1.009	1.011	1.062	1.010
Monetary-based model				
t+1	1.000	**0.998**	**0.970***	**0.998**
t+2	1.005	1.006	**0.953***	1.007
t+3	**0.996**	1.001	**0.968**	**0.996**
t+4	**0.989**	**0.992**	1.005	**0.990**
Taylor-rule model				
t+1	**0.970**	**0.977**	**0.949****	**0.963**
t+2	1.004	1.004	**0.971***	1.002
t+3	**0.999**	**0.997**	**0.987**	**0.999**
t+4	1.000	**0.999**	1.016	**0.999**

Notes: Table 4.6 reports the relative Root Mean Squared Forecast Errors (RMSFE) between the above mentioned BVAR(1) models and the benchmark random walk model without drift. Ratios in **bold** indicate the cases in which the null hypothesis of equal predictive accuracy (one-sided CW07 test) is rejected against the alternative of outperforming the benchmark RW model at the 1% (***), 5% (**) and 10% (*) significance levels.

4.5 Concluding remarks

Based on the theoretical modelling of the exchange rate returns, we employ the foreign policy crisis as an approximation for the changes in countries' disaster risk and as an additional predictor for the FX rate returns. We use an extensive data set that includes all the foreign policy crises of different severity and violence of the U.S. and the U.K, to empirically examine if the changes in the disaster risk affect and predict the nominal USD/GBP returns.

We find that, in both in-sample and out-of-sample analyses, foreign policy crises can be useful in predicting the future path of the exchange rate returns. We should note that, among all crises variables, the ongoing FPCs have been proved the most significant and informative predictors, as the adjusted R^2 and relative RMSFEs indicate. By employing these predictors, the predictive power of the augmented monetary-based and Taylor rule models is increased and the forecasting performance of our models exceeds that of the random walk, especially at shorter horizons. On the other hand, the augmented PPP-based and Fama-based models provide less evidences that the crises variables can predict the exchange rate returns.

Chapter 5

Conclusions

This thesis examines the behaviour, predictive content and predictability of the nominal USD/GBP exchange rate changes, as well as their relationship with the foreign policy crises of the U.S. and the U.K. We conduct both in-sample and out-of-sample analysis, paying attention to the unstable and time-varying relationship between the economic variables, and using vintage data for the variables that suffer from consecutive revisions.

Chapter 2 reviews the predictive content of the nominal exchange rate returns by novelly extending the empirical work of Engel and West (2005) in three directions: i) building an out-of-sample forecasting exercise in an attempt to generate forecasts for the Taylor rule fundamentals (output gap, inflation, and real exchange rate), ii) employing time-varying parameter models, taking into account the possible asymmetric preferences, non-linearities, and instabilities that real world faces, and iii) employing real-time data.

We begin our empirical work with a structural break analysis of the U.S. and U.K. monetary policy rules, with results suggesting the usage of TVP models in the subsequent forecasting exercise. Then, to draw a priori more predictive power from the exchange rates changes than the rest predictors, we employ a homoscedastic Bayesian TVP-VAR model with the appropriate restrictive priors for forecasting the Taylor rule fundamentals. We show that our model generates significant real-time forecasts for the U.S. output gap at the 1-, 2-, 3- and 4-quarter-ahead horizons, the U.K. output gap at the 3- and 4-quarter-ahead horizons and the U.K. real exchange rate at 1-quarter-ahead horizon, as well as for the U.K. inflation using a rolling scheme. The main conclusion that emerges from this analysis is that the finding of Engel and West (2005), that the exchange rate changes can predict, in-sample, the Taylor rule fundamentals, can also be confirmed by our out-of-sample exercise where our methods are applied.

Chapter 3 examines the second topic of this thesis, which is the forecastability of the nominal USD/GBP exchange rate returns by using theoretical and empirical models. This analysis begins with a critical survey of the existing exchange rate literature, presenting all the traditional theoretical models and some less known empirical FX models and reporting their in-sample and out-of-sample performance. Largely inspired by the 'Meese and Rogoff' puzzle, we test a wide variety of fundamentals-based models in an attempt to examine the well-known 'disconnection' between the FX changes and the macroeconomic fundamentals in an out-of-sample environment.

The contribution to the literature is twofold. First, we show that considering for the non-linearities and time-variation in both parameters and innovations does not always deliver better FX forecasts. We find that the linear BVAR model with a Minnesota prior can compete and sometimes perform better than the heteroscedastic TVP-BVAR model, delivering more accurate forecasts. We therefore support the view that this specific econometric model should become a benchmark model in the FX forecasting literature. Second, we find that of the five fundamentals-based models, the most successful is the PPP-based model, outperforming the benchmark driftless random walk model, especially at the short-horizon, while the DSGE model cannot deliver reliable forecasts. In addition, inspired by the 'scapegoat' theory, we examine the predictive relevance of 15 macroeconomic fundamentals, using the Dynamic Model Selection and Averaging. We find that the most relevant predictors during the out-of-sample period, in forecasting the FX returns at the 1-quarter-ahead horizon, are the 1-month and 3-month forward premiums and the U.S. money supply.

The last topic of this thesis, which examines the predictive relationship between the USD/GBP exchange rate returns and the foreign policy crises of the U.S. and the U.K., is covered in Chapter 4. Motivated by the disaster risk literature, we use the foreign policy crises as an approximation for the time-varying disaster risk of the U.S. and U.K. economies, examining their in-sample and out-of-sample predictive impact on the FX changes. We find that once the crises predictors are combined with the monetary and Taylor rule fundamentals, the in-sample explanatory power of the exchange rate models is increased, as measured by the adjusted R^2. We also see how the FX returns are affected by the crises of different actors-states, severity and violence. Finally, we find that, among different specifications, the models which significantly forecast the FX changes and outperform the random walk model in out-of-sample accuracy are the monetary-based and Taylor rule-based models including the ongoing crises as extra predictors.

In this thesis we have not considered any models based on the microeconomic fundamentals, such as the order flows, to forecast the future FX changes. Moreover, it is worth investigating the in-sample and out-of-sample forecasting power of the exchange rates changes to predict the microeconomic fundamentals. We hence leave these topics for future research.

Appendix A

<u>**Bai and Perron (1998, 2003) test**</u>

Considering a multiple linear regression system with *m* breaks (*m* + 1 regimes) in matrix form as:

$$Y = X\beta + Z\alpha + U \; , \tag{A.1}$$

where $Y = (y_1,.., y_T)'$ collects the dependent variable, $X = (x_1,.., x_T)'$ are regressors whose β coefficients do not vary across regimes, $Z = diag(Z_1,.., Z_{m+1})$ collects the explanatory variables with regime-specific parameters $a = (a_1^{'},..., a_{m+1}^{'})'$, and *U* collects the error terms. For each *m*-partition ($T_1,\ldots,T_m$), the sum of squared residuals is minimised to obtain the least-squares estimates of β and α such as:

$$(Y - X\beta - Z\alpha)'(Y - X\beta - Z\alpha) = \sum_{i=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_i} [y_t - x'\beta - z_t'\alpha_i]^2 \; . \tag{A.2}$$

If we plug the estimated parameters of this partial structural change model into the objective function, we obtain the resulting sum of squared residuals as: $S_T(T,....., T_m)$, and then the estimated break point $(\hat{T}_1,...., \hat{T}_m)$ is obtained by minimising the *SSR* and using dynamic programming over all the partitions. That is,

$$(\hat{T}_1,...., \hat{T}_m) = \arg\min_{T_1,...,Tm} S_T(T_1,...., T_m) \; .$$

Bai and Perron (2003) construct several test statistics for examining possible multiple structural breaks in pure structural change models where all parameters are allowed to change.

<u>SupF test of no structural breaks (*m* = 0) versus a fixed number of m breaks (*m* = *k*)</u>

Under this test we test the null hypothesis of zero structural breaks against the alternative of *k* changes. Regarding the null hypothesis, the model is estimated over the full sample, while under the alternative, model is estimated on each sub-sample of dimension $T_i = \lambda_i T$ (for i=1,…,k). So, the following F-type test is calculated as:

$$F_T(\lambda_1,\ldots\ldots,\lambda_k;q) = \frac{1}{T}\left(\frac{T-(k+1)q-p}{kq}\right)\hat{\alpha}'R'(R\hat{V}(\hat{a})R')^{-1}R\hat{\alpha}\,, \qquad \text{(A.3)}$$

where $\hat{V}(\hat{a})$ is an estimate of the variance covariance matrix of $\hat{\alpha}$ and robust to serial correlation and heteroscedasticity such as:

$$\hat{V}(\hat{a}) = p\lim T(Z'M_X Z)^{-1}Z'M_X\,\Omega M_X\,Z(Z'M_X\,Z)^{-1},$$

with $\Omega = \mathrm{E}(UU')$ and $M_X = I - X(X'X)^{-1}X'$. So the *supF* test is then based upon the following statistic:

$$\sup F_T(k;q) = F_T(\hat{\lambda}_1,\ldots,\hat{\lambda}_k;q). \qquad \text{(A.4)}$$

<u>Double maximum tests, Bai and Perron (1998)</u>

A test in which the null hypothesis of no breaks is tested against the hypothesis of an unknown number of breaks given an upper bound M. Given some fixed weights $\{a_1,\ldots,a_M\}$ defined a priori, $D_{\max}F_T(M,q,\alpha_1,\ldots\ldots,\alpha_{\mathrm{M}}) = \max_{1\le m\le M} a_m \sup F_T(\hat{\lambda}_1,\ldots,\hat{\lambda}_m;q)$ with q degrees of freedom. Two versions of the test are defined; in the first one, all weights are set equal to 1 and this is reduced to:

$$UD_{\max}\; F_T(M,q) = \max_{1\le m\le M} \sup F_T(\hat{\lambda}_1,\ldots,\hat{\lambda}_m;q)\,, \qquad \text{(A.5)}$$

where $\hat{\lambda}_j = \hat{T}_j / T$ are the estimates of the breaks for j = (1,….,m). But, if the weights assigned are set such that the marginal p-values are equal across the breaks, then the test is called $WD_{\max}\,F_T(M,q)$.

Clark and West (2006, 2007) test

The Clark and West (2007) test uses two nested models:

$y_t = X'_{1t}\beta_1 + \varepsilon_{1t}$ (null model)

$y_t = X'_{2t}\beta_2 + \varepsilon_{2t}$ (alternative model),

where X'_{1t} is a subset of X'_{2t}, with forecast errors $fe^1{}_{t+1|t} = y_{t+1} - X'_{1t+1}\hat{\beta}_{1t}$ and $fe^2{}_{t+1|t} = y_{t+1} - X'_{2t+1}\hat{\beta}_{2t}$ and their mean squared forecast errors are given by: $\hat{\sigma}_1^2 = \frac{1}{\mathrm{T}_0}\sum_{t=t_0}^{\mathrm{T}}\left(fe^1_{t+1|t}\right)^2$ and $\hat{\sigma}_2^2 = \frac{1}{\mathrm{T}_0}\sum_{t=t_0}^{\mathrm{T}}\left(fe^2_{t+1|t}\right)^2$, where forecasts are computed for $t = t_0,...,T$ and T_0 is the number of forecasts. Hence, the one-sided CW tests the hypothesis:

$$H_0: \quad \hat{\sigma}_1^2 - \hat{\sigma}_2^2 = 0$$

$$H_1: \quad \hat{\sigma}_1^2 > \hat{\sigma}_2^2 \,.$$

CW constructs a test statistic by adjusting the sample MSFE of the alternative model, such as $\sigma_2^2 = \hat{\sigma}_2^2 - \frac{1}{\mathrm{T}_0}\sum_{t=t_0}^{\mathrm{T}}(X'_{1t+1}\hat{\beta}_{1t} - X'_{2t+1}\hat{\beta}_{2t})^2$.

So, for an adjusted $\hat{f}_{t+1} = \left(fe^1_{t+1|t}\right)^2 - \left[\left(fe^2_{t+1|t}\right)^2 - \left(X'_{1t+1}\hat{\beta}_{1t} - X'_{2t+1}\hat{\beta}_{2t}\right)^2\right]$, $\bar{f} = \frac{1}{T_0}\sum_{t=t_0}^{T}\hat{f}_{t+1}$ and $\hat{V} = \frac{1}{T_0}\sum_{t=t_0}^{T}\left(\hat{f}_{t+1} - \bar{f}\right)^2$, the statistic $CW = \bar{f}\left(\sqrt{\frac{\hat{V}}{T_0}}\right)^{-1}$. The above test is also used in Clark and West (2006), where the null model is represented by a zero mean martingale difference model. In that case, the one-step-ahead prediction of the null model is always 0, changing the forecast errors and the adjusted terms accordingly. The authors argue that this is an asymptotically standard normally distributed statistic, and thus, the null hypothesis is rejected at the 5% significance level when the test statistic is greater than 1.645.

Table A.1: Clark and West (2006) test statistics of Table 2.3

	TVP-BVAR(1) -RW	BVAR(1) - RW	VAR (1) - RW
y_{t+1}^{gap}	3.385	2.213	2.074
y_{t+2}^{gap}	2.579	1.972	1.882
y_{t+3}^{gap}	2.688	2.155	2.092
y_{t+4}^{gap}	3.197	2.354	2.310
y_{t+1}^{fgap}	0.686	2.074	2.084
y_{t+2}^{fgap}	1.395	1.753	1.750
y_{t+3}^{fgap}	1.180	1.829	1.818
y_{t+4}^{fgap}	1.473	1.924	1.915
π_{t+1}	0.244	1.201	1.158
π_{t+2}	1.074	0.894	0.875
π_{t+3}	1.784	0.777	0.772
π_{t+4}	0.991	0.563	0.554
π_{t+1}^{f}	-1.734	1.983	1.973
π_{t+2}^{f}	-1.384	1.882	1.878
π_{t+3}^{f}	-0.542	1.630	1.617
π_{t+4}^{f}	-0.608	1.901	1.885
q_{t+1}^{f}	1.810	1.633	1.572
q_{t+2}^{f}	0.731	0.912	0.907
q_{t+3}^{f}	-0.321	1.005	1.026
q_{t+4}^{f}	-0.393	1.231	1.243

Notes: Table reports the Clark and West (2006) test statistics of Table 2.3.

Table A.2: Clark and West (2006) test statistics of Table 2.5

	TVP-BVAR(1) -RW	BVAR(1) - RW	VAR (1) - RW
y_{t+1}^{gap}	3.755	1.489	1.085
y_{t+2}^{gap}	2.475	1.399	1.203
y_{t+3}^{gap}	2.006	1.618	1.496
y_{t+4}^{gap}	1.889	1.771	1.663
y_{t+1}^{fgap}	1.245	1.472	1.630
y_{t+2}^{fgap}	1.391	1.340	1.539
y_{t+3}^{fgap}	1.280	1.511	1.650
y_{t+4}^{fgap}	1.375	1.654	1.719
π_{t+1}	0.739	-1.465	-1.637
π_{t+2}	0.955	-1.083	-1.235
π_{t+3}	0.757	-0.760	-0.847
π_{t+4}	0.022	-0.364	-0.379
π_{t+1}^{f}	0.794	1.678	1.637
π_{t+2}^{f}	0.626	1.953	1.912
π_{t+3}^{f}	1.297	1.673	1.631
π_{t+4}^{f}	1.182	1.814	1.782
q_{t+1}^{f}	1.727	2.306	2.460
q_{t+2}^{f}	1.342	1.936	2.054
q_{t+3}^{f}	-0.397	1.710	1.838
q_{t+4}^{f}	-0.611	1.509	1.799

Notes: Table reports the Clark and West (2006) test statistics of Table 2.5.

Appendix B

BVAR(p) model as in Korobilis (2013) [55]

If we keep Korobilis's (2013) notation then we can write the reduced form VAR model as:

$$y_t = c + B_1 y_{t-1} + B_2 y_{t-2} + B_3 y_{t-3} + \dots\dots\dots + B_p y_{t-p} + \varepsilon_t\,, \qquad \text{(B.1)}$$

where p is the number of lags, y_t is an $m\times 1$ vector of $t = 1,\dots,T$ observations collecting the explanatory variables, errors $\varepsilon_t \sim N_m(0,\Sigma)$ where Σ is the covariance matrix of $m\times m$ dimension and m is the number of variables. The model can also be re-written in the following form:

$$y_t = z_t\beta + \varepsilon_t\,, \qquad \text{(B.2)}$$

where $z_t = I_m \otimes x_t = I_m \otimes \left(1, y_{t-1},\dots, y_{t-p}\right)'$ is an $m\times n$ matrix, β is the $n\times 1$ state vector $\left[c', vec\left(B_1'\right),\dots, vec\left(B_p'\right)\right]'$ of parameters, $n = mk$ and $k = mp + 1$. This linear BVAR model is accompanied by the *Minnesota prior* specification (see Litterman, 1986; Doan et al., 1984). This kind of prior assumes:

$$\beta \sim N\left(\underline{\beta}_{Min}, \underline{V}_{Min}\right)\,, \qquad \text{(B.3)}$$

where the prior mean follows a random walk behaviour. In other words, it gives a value of 1 for parameters of the first own lag of the dependent variable of each equation and a zero value for the rest. As regards the prior variance of the parameters, a diagonal matrix $\left(\underline{V}_{Min}\right)$ is assumed, with a prior of $100\,s_i^2$ for the intercepts, $1/r^2$ for their own lagged coefficients and $\lambda s_i^2 / r^2 s_l^2$ otherwise, where $r = 1,\dots,p$, $i = 1,\dots,m$, $j = 1,\dots,k$, s_i^2 is the residual variance from the unrestricted univariate AR(p) regression for variable i, and $\lambda = 0.1$ is a hyperparameter that controls the shrinkage level. A non-informative prior for Σ has been assigned, $\left(\underline{S} = \underline{\nu} = 0\right)$.

[55] The original Matlab codes of all the Bayesian models employed in this thesis can be found in Prof. Korobilis's webpage, at: https://sites.google.com/site/dimitriskorobilis/matlab.

The conditional posterior for β can be obtained using the Normal distribution, like:

$$\beta \mid \Sigma, y \sim N\left(\overline{\beta}_{Min}, \overline{V}_{Min}\right), \tag{B.4}$$

where the posterior variance $\overline{V}_{Min} = (\underline{V}_{Min}^{-1} + z'Vz)^{-1}$, with $V = \hat{\Sigma}^{-1} \otimes \mathrm{I}_m$ and $\hat{\Sigma}^{-1}$ is the OLS estimate of Σ. The posterior mean for the parameters is given from $\overline{\beta}_{Min} = \overline{V}_{Min}(\underline{V}_{Min}^{-1}\underline{\beta}_{Min} + z'Vy)$. The posterior for Σ is obtained using the inverse Wishart density, as:

$$\Sigma^{-1} \mid y, \beta \sim Wishart\left(\overline{v}, \overline{S}^{-1}\right), \tag{B.5}$$

where $\overline{S} = \underline{S} + (y - x\beta)'(y - x\beta)$ and $\overline{v} = T + \underline{v}$. Bayesian inference is obtained using the Gibbs sampler as an MCMC method.[56]

Homoscedastic TVP-BVAR(p) model

The model can be written in the following linear state-space form:

$$y_t = z_t\beta_t + \varepsilon_t \tag{B.6}$$

$$\beta_t = \beta_{t-1} + \eta_t, \tag{B.7}$$

where y_t collects the dependent variables, z_t the lagged data, and β_t the time-varying parameters, while $\eta_t \sim N(0, Q)$ and $\varepsilon_t \sim N(0, \Sigma)$ do not correlate with each other. Please refer to the main text for more detail and the priors.

Posteriors

Before we set up the Gibbs sampling algorithm with the Kalman filter and smoother, we need to specify the full conditional posterior distribution of $\widehat{\beta}_T$ for all states (unobserved TVPs), conditioning on data y_T (for all time periods), Σ and Q as:

[56] As Koop and Korobilis (2009) state, when Σ is replaced by an OLS estimate then an analytical solution is given. But when Σ is treated as an unknown parameter, then an MCMC method for sampling from the posterior conditional distribution is required.

$$p\left(\widehat{\beta}_T \mid y_T, \Sigma, Q\right) = p\left(\beta_T \mid y_T\right) \prod_{t=1}^{T-1} p\left(\beta_t \mid y_T, \beta_{t+1}\right). \tag{B.8}$$

The conditional posterior density of Q conditioning on data, parameters and Σ is given by:

$$Q^{-1} \mid \beta_T, z_T, y_T, \Sigma \sim Wishart\left(\overline{R}^{-1}, \overline{\xi}\right), \tag{B.9}$$

where $\overline{\xi} = \underline{\xi} + T$ and $\overline{R}^{-1} = \left(\underline{R} + \sum_{t=1}^{T}\left(\beta_t - \beta_{t-1}\right)\left(\beta_t - \beta_{t-1}\right)'\right)^{-1}$. Also, $\underline{\xi} = (n+1)2$ are the degrees of freedom (n is the number of parameters in the state vector) and $\underline{R} = k_R I_n$ where k_R is the scaling factor and equal to 0.0001. The posterior density of Σ conditional on data, parameters and Q is given by:

$$\Sigma^{-1} \mid y_T, \beta_T, Q \sim Wishart\left(\overline{J}^{-1}, \overline{v}\right), \tag{B.10}$$

where $\overline{J} = \underline{J} + \sum_{t=1}^{T}\left(y_t - z_t\beta_t\right)\left(y_t - z_t\beta_t\right)'$, $\overline{v} = \underline{v} + T$, and T is the sample size.

<u>Carter and Cohn (1994) algorithm</u>

To draw samples for parameters β_t for $t = 1,...,T$, we use the Carter and Kohn (1994) algorithm within the Gibbs sampler. This approach is used by Korobilis (2013) and slightly differently by Byrne et al. (2016). The Kalman filter runs recursively through the data to obtain the mean and the covariance of the conditional posterior $p(\beta_T | y_T)$, along with the means and covariances of betas at every time period $t = 1,2,\ldots,T$. Let us denote $\beta_{0|0}$ and $P_{0|0}$ as the initial values for the mean and the covariance along with $\beta_{t|s}$ and $P_{t|s}$ the corresponding expected value and covariance, conditional on information up to time s (i.e. for a process running from 1 to t, then, $\beta_{t|s} = E(\beta_t | y_s) = E(\beta_t | y_{1,2,\ldots,s})$)[57]. Also, we should note that $\beta_{t-1|t-1} = \beta_{t|t-1}$, since we assume that beta coefficients evolve according to a driftless random walk with slope equal to 1 and $P_{t-1|t-1} = P_{t|t-1} - Q$.

[57] It is also very common practice to use a training sample with a VAR model and use the OLS estimated parameters as priors for Kalman filter's initial conditions.

First step of the algorithm is the Kalman filter

Kalman filter

First step: The first step is to define the initial values (priors) for t=0 as defined above for the initial state ($\beta_{0|0}$ and $P_{0|0}$).

Second step: For $t = 1$, we need to predict the state vector along with its covariance matrix: $\beta_{1|0} = \beta_{0|0}$ and $P_{1|0} = P_{0|0} + Q$.

Third step: Next we predict the $y_{1|0}$ and subtract it from the observed data y_1 at t =1 so that we obtain the conditional forecast error $cfe_{t|t-1}$ along with its covariance matrix $f_{t|t-1}$. We calculate them as:

$$
\begin{gathered}
y_{t|t-1} = z\beta_{t|t-1}\,, \\
cfe_{t|t-1} = y_t - y_{t|t-1}\,, \\
f_{t|t-1} = zP_{t|t-1}z' + \Sigma.
\end{gathered}
$$

Forth step: The prediction error will help to revise the initial inference about the beta at t =1 through the Kalman gain (K_t), where $K_t = P_{t|t-1}z'\left(f_{t|t-1}\right)^{-1}$. Then, the Kalman gain which is the weight representing the uncertainty of the new information, will help us to revise the inference about $\beta_{t|t}$ and $P_{t|t}$, given that:

$$
\begin{gathered}
\beta_{t|t} = \beta_{t|t-1} + K_t cfe_{t|t-1}\,, \\
P_{t|t} = P_{t|t-1} - K_t zP_{t|t-1}\,.
\end{gathered}
$$

At the fifth step, the filter (steps 2–4) is repeated for all time periods t = 2, 3, 4,…..,T and then the Kalman filter ends. [58]

Second step: Smoothing procedure

At the end of the filtering process, we end up with the last state $\beta_T \left| y_T \right.$, but for the previous states we have obtained the distributions of betas conditional only on a subset

[58] More analytical derivation of the Kalman filter's updating equations can be found in Kim and Nelson (1999, p.22).

of the data (Karlsson, 2013). This means that not all of the available information has been used and a backward recursion is needed to smooth our Kalman filter estimates obtained previsouly. So, for the periods *T*-1,*T*-2,….,1 the smoother runs backward through data obtaining the smoothed estimates.

First step: We draw $\tilde{\beta}_T \sim N(\beta_{T|T}, P_{T|T})$.

Second step: For $t = T-1$, we calculate $\beta_{T-1|T-1,\beta_T} = \beta_{T-1|T-1} + \mathrm{K}(cfe)$, where $cfe = \tilde{\beta}_T - \beta_{T-1|T-1}$ and $P_{T-1|T-1,\beta_T} = P_{T-1|T-1} - \mathrm{K}P_{T-1|T-1}$, where both $\beta_{T-1|T-1}$ and $P_{T-1|T-1}$ were obtained from the Kalman filter stage for $t = T-1$.

Third step: We repeat the second step until t = *T*-2, *T*-3,…,1. What we collect at the end of the backward recursions is the sample of time-varying betas of Gibbs first iteration. We can call it β_t.

Since we obtained the sample of betas (β_t), we can now use them to draw samples for Σ and Q from their conditional distributions. First, we draw samples for the covariance matrix of the transition equation (Q) from the conditional posterior distribution which is the inverse Wishart, as in eq. (B.9). Next, we can draw samples for the covariance matrix (Σ) of the measurement equation from the inverse Wishart as well, conditional on information as in eq. (B.10).

We should not take it for granted that Gibbs sampler converges to the posterior distribution, nor that it converges after a reasonable number of iterations to a reliable point estimate. One way to see whether the sampler converges and how fast (i.e. how well our chain is mixing and moves around the parameter space), is by simply plotting the draws of the parameter against the number of iterations (traceplots). Then, we can discern through visual inspection whether the chain gets stuck at specific areas of the parameter space or how many iterations are needed (i.e. how fast) in order to converge to the desired posterior density. For all the Bayesian VAR models, estimation is based on 20,000 draws after discarding the first 5,000 to ensure a convergence. We also thin the chain by keeping only the every tenth draw in order to mitigate the autocorrelation in the Markov chain. In the end we obtain the mean of the marginal conditional posterior distribution as the point estimate of β_t.

Heteroscedastic TVP- BVAR(p) model

We set our priors as in Primiceri (2005), where a time-invariant VAR model of size $\tau = 40$ is used to calibrate them. Also, a normal prior for the coefficients and the log σ_t and the inverse Wishart and Gamma for the hyperparameters Q, W, S_1 and S_2. Note that the model assumes a block diagonal matrix for S to ensure the independency of the variables' parameters evolution.[59] So, assuming for simplicity two blocks for S:

Priors

$$
\begin{aligned}
\beta_0 &\sim N(\hat{\beta}_{OLS}, 4\cdot V(\hat{\beta}_{OLS})),\\
A_0 &\sim N(\hat{A}_{OLS}, 4\cdot V(\hat{A}_{OLS})),\\
\log\sigma_0 &\sim N(\log\hat{\sigma}_{OLS}, I_m),\\
Q &\sim IW(0.01^2\cdot 40\cdot V(\hat{\beta}_{OLS}), 40),\\
W &\sim IG(0.001, 8),\\
S_1 &\sim IW(0.1^2\cdot 2\cdot V(\hat{A}_{1,OLS}), 2),\\
S_2 &\sim IW(0.1^2\cdot 3\cdot V(\hat{A}_{2,OLS}), 3),
\end{aligned}
$$

where the variance of β_0 and A_0 are four times the variance of the OLS estimates and the log of the OLS estimates for the σ_0. The degrees of freedom of the inverse Wishart densities is equal to 1 plus the dimension of the matrices and 40 (size of the training sample) for the Q.

Posteriors

The Bayesian inference can be obtained sequentially using the Gibbs sampler by:

a) Drawing samples for the β^T conditional on $y^T, \mathrm{A}^T, \Sigma^T, V$ using the Carter and Kohn (1994) algorithm which employs the Kalman filter along with a smoothing process, using the initial conditions as described above.
b) Sampling A^T from the conditional density $p(\mathrm{A}^T | y^T, \beta^T, \Sigma^T, V)$ using the Carter and Kohn (1994) algorithm which employs the Kalman filter along with a smoothing process. Further transformations are needed since the model has a

[59] The number of the diagonal blocks in S is equal to the number of the observed variables minus one.

Gaussian but non-linear form (see Primiceri's (2005) Appendix for more details).

c) In order to draw samples for Σ^T, further modifications are needed to bring the model into a linear and Gaussian form. The innovations of the measurement equations are distributed as a log χ^2 and a mixture of their normal approximation is used as in Kim et al. (1998). Defining and sampling s^T, which is a matrix of indicator variables that governs the Gaussian approximations, the system now becomes normal and linear, and the conditional posterior of Σ^T is obtained.

d) Finally, the posterior density for the diagonals of V conditional on y^T, A^T, Σ^T, B^T can be drawn from the inverse Wishart and inverse Gamma distributions. For draws from the $IW(\overline{S}, \overline{V})$ density:

$$\overline{S}^{Q^{-1}} = \left(\underline{S}^Q + \sum_{t=1}^{T} (\beta_t - \beta_{t-1})(\beta_t - \beta_{t-1})' \right)^{-1} \text{ and } \overline{V}^Q = t + \underline{V}^Q,$$

$$\overline{S}^{S_{1,2}{}^{-1}} = \left(\underline{S}^{S_{1,2}} + \sum_{t=1}^{T} (\mathrm{A}_t - \mathrm{A}_{t-1})(\mathrm{A}_t - \mathrm{A}_{t-1})' \right)^{-1} \text{ and } \overline{V}^{S_{1,2}} = t + 1 + size(S_{blocks}).$$

For draws for the W matrix from the $IG\left(\frac{\overline{u}}{2}, \frac{2}{\overline{\delta}}\right)$ density:

$$\overline{u} = \underline{u} + t - p - 1 \text{ and } \overline{\delta} = \underline{\delta} + \sum_{t=1}^{T} \left(\Delta \ln \sigma_t\right)^2, \text{ where } \underline{u} = 8 \text{ and } \underline{\delta} = 0.001.$$

Priors for the sensitivity analysis

For the purposes of the sensitivity analysis we set the following non-informative priors:

$$\beta_0 \sim N(0, I_K),$$
$$A_0 \sim N(0, I_g),$$
$$\log \sigma_0 \sim N(0, I_m),$$
$$Q \sim IW(0.01^2 \cdot V(\beta_0), 40),$$
$$W \sim IG\left(\frac{0.01^2}{2}, \frac{1}{2}\right),$$
$$S_1 \sim IW(0.1^2 \cdot 2 \cdot V(A_0), 2),$$

$$S_2 \sim IW(0.1^2 \cdot 3 \cdot V(A_0), 3),$$

where $K = m + pm^2$ and $g = m(m-1)/2$. The sampling process and specifications remain the same, except for *W*, which is drawn from the $IG\left(\frac{\overline{u}}{2}, \frac{\overline{\delta}}{2}\right)$ density with $\overline{u} = \underline{u} + T - p - 1$ and $\overline{\delta} = \underline{\delta} + \sum_{t=1}^{T} (\Delta \ln \sigma_t)^2$.

Dynamic Model Averaging and Selection

We closely follow the DMA model developed by Raftery et al. (2010) and Koop and Korobilis (2012, 2013) in a heteroscedastic TVP-AR specification. The state space model can be written as:[60]

$$y_t = z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)} \tag{B.11}$$

$$\theta_t^{(k)} = \theta_{t-1}^{(k)} + \eta_t^{(k)}$$

where y_t is the log of exchange rate change, k = 1 ,….., K is the number of models, each using a different set of predictors, $z_t^{(k)}$ is a matrix of predictors where each of these k models uses and $\theta_t^{(k)}$ collects the corresponding coefficients. Also, $\varepsilon_t^{(k)} \sim N(0, H_t^{(k)})$ and $\eta_t^{(k)} \sim N(0, Q_t^{(k)})$. Following Korobilis' (2012) notation, let $\Theta_t = (\theta_t^{(1)'}, \ldots, \theta_t^{(k)'})'$, $y_t = (y_t, \ldots, y_t)'$ and $L_t \in \{1, 2, \ldots, K\}$ indexing which model specification holds in each time period. First, we need to specify the prior mean and variance for the parameters, which are based on the data (as in Raftery et al., 2010). The prior mean has been set equal to zero $\left(\hat{\theta}_0^{(k)} = 0\right)$ and prior variance: $\Sigma_0^{(k)} = \mathrm{diag}\left(s_1^{2(k)}, \ldots, s_{\mathrm{K}}^{2(k)}\right)$, where $s_j^{2(k)} = \mathrm{Var}(y_t) / \mathrm{Var}(z_{t,j}^{(k)})$ and $j = 2, \ldots, K$. Regarding the prior of the single-model probability $\pi_{0|0,k} = 1/K$ implying that all models are initially equally weighted.

---

[60] This is actually a TVP-ARX model (as in Ljung, 1987), which allows for both lags of the independent and exogenous variables to predict.

Posterior inference –Kalman filter

Below we present the modified Kalman filter, taking into account the multiple model case that we face in the DMA and DMS models and the fact that we replace some components with their estimates. So, given the priors (initial conditions), filter predicts the parameters of each state, conditional on model $L_t = k$ and information up to t – 1:

$$\theta_{t-1}^{(k)} \mid L_{t-1} = k, y^{t-1} \sim N(\hat{\theta}_{t-1|t-1}^{(k)}, \Sigma_{t-1|t-1}^{(k)}) \quad \text{and predicts}$$

$$\theta_{t}^{(k)} \mid L_{t} = k, y^{t-1} \sim N(\hat{\theta}_{t|t-1}^{(k)}, \Sigma_{t|t-1}^{(k)}) \text{ , where } \hat{\theta}_{t|t-1}^{(k)} = \hat{\theta}_{t-1|t-1}^{(k)}$$

and $\Sigma_{t|t-1}^{(k)} = \Sigma_{t-1|t-1}^{(k)} + Q$. Raftery et al. (2010) employ the forgetting factor λ in order to avoid simulating Q and approximate directly:

$$\Sigma_{t|t-1}^{(k)} = \frac{1}{\lambda} \Sigma_{t-1|t-1}^{(k)} \tag{B.12}$$

where $\lambda \in (0,1]$. A value of 0.99 (using quarterly data) implies that the observations from the previous five years will bear 80% as much weight as the last quarter's observation. This factor also implies a smooth evolution of the parameters. Hence, there is no need to simulate Q and the computation time is reduced significantly. What follows is the standard equations for the prediction errors and their conditional variance, and, finally, the updating equations for the coefficients and their covariance matrix conditional on information up to t. To be more specific:

$$\theta_{t}^{(k)} \mid L_{t} = k, y^{t} \sim N(\hat{\theta}_{t|t}^{(k)}, \Sigma_{t|t}^{(k)}) \tag{B.13}$$

where $$\hat{\theta}_{t|t}^{(k)} = \hat{\theta}_{t|t-1}^{(k)} + \Sigma_{t|t-1}^{(k)} z_t'^{(k)} \left(H_t^{(k)} + z_t^{(k)} \Sigma_{t|t-1}^{(k)} z_t'^{(k)} \right)^{-1} \left(y_t - z_t^{(k)} \hat{\theta}_{t|t-1}^{(k)} \right)$$

and $$\Sigma_{t|t}^{(k)} = \Sigma_{t|t-1}^{(k)} - \Sigma_{t|t-1}^{(k)} z_t'^{(k)} \left(H_t^{(k)} + z_t^{(k)} \Sigma_{t|t-1}^{(k)} z_t'^{(k)} \right)^{-1} z_t^{(k)} \Sigma_{t|t-1}^{(k)} .$$

Furthermore, this model requires a probabilistic mechanism dictating which model k is applied in each time period. Koop and Korobilis (2012) state that a standard way of doing this is to use a transition probability matrix $P = (p_{kl})$ of $K \times K$ dimensions with elements $p_{kl} = \Pr(L_t = l \mid L_{t-1} = k)$ where $k, l = 1,..., K$. The problem with this approach is that in a case where a large number of m potential predictors is used, a huge transition

P matrix with $K = 2^m$ is formed, increasing the computational burden. Raftery et al. (2010) in order to avoid specifying matrix *P* they replace it with an approximation, introducing another forgetting factor *a* with the same properties and interpretation as *λ*. So, the probability for model *k* to contribute in the exchange rate forecasting exercise conditional on data, is given by $\pi_{t-1|t-1,k} = \Pr\left[L_{t-1} = k \middle| y^{t-1}\right]$. At $t = 0$ the prior probability (which is the initial condition of the Kalman filter) is $\pi_{0|0,k} = 1/K$ entailing all models being equally weighted in predicting the FX changes. Then, the probability for model *k* to predict at time *t* conditional on information up to *t*-1 is calculated using the forgetting factor *α*, such as:

$$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^{a}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{a}}, \tag{B.14}$$

and probability is updated recursively using the following equation:

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k}\, p_k(y_t | y^{t-1})}{\sum_{l=1}^{K} \pi_{t|t-1,l}\, p_l(y_t | y^{t-1})}, \tag{B.15}$$

where $p_k(y_t | y^{t-1})$ is the predictive likelihood of model *k* evaluated at *t*-1. Hence model *k* receives the appropriate weight, taking into account the forecasting performance of the model in the 'recent past' as measured by the predictive density. The term 'recent past' is governed by the factor *α*. For example if, $\alpha = 0.99$, the five-years ago forecasting performance of model *k* will receive around 80% as much weight as the performance of the last quarter (Koop and Korobilis, 2012). Regarding the covariance matrix $H_t^{(k)}$, Koop and Korobilis (2012) uses an Exponentially Weighted Moving Average (EWMA) estimate:

$$\hat{H}_t^{(k)} = \sqrt{(1-\kappa)\sum_{j=1}^{t} \kappa^{j-1}\left(y_j - z_j^{(k)}\hat{\theta}_j^{(k)}\right)^2}, \tag{B.16}$$

where κ is a decay factor equal to 0.98. Finally, given the weight π that each model bears, DMA generates direct forecasts recursively as:[61]

$$\hat{y}_t^{DMA} = \sum_{k=1}^{K} \pi_{t|t-1,k} z_t^{(k)} \hat{\theta}_{t-1}^{(k)}, \tag{B.17}$$

while DMS chooses the single model $g \in \{1,2,\ldots,K\}$ with the highest probability and forecasts as:

$$\hat{y}_t^{DMS} = z_t^{(g)} \hat{\theta}_{t-1}^{(g)}. \tag{B.18}$$

<u>DSGE model's micro-foundations</u>

The open economy model is based on Monacelli (2005), Gali and Monacelli (2005), Justiniano and Preston (2010), Steinbach et al. (2009) and Alpanda et al. (2011). The U.S. represents the domestic economy and U.K. the foreign one.

Households and optimal wage

The domestic economy consists of infinitely-lived households (followed by an index *i*, where $i \in [0,1]$) consuming both domestically produced $(C_{h,t})$ and imported goods $(C_{f,t})$, where the composite consumption index is given by:

$$C_t \equiv \left[(1-\gamma)^{\frac{1}{\eta}} C_{h,t}^{\frac{\eta-1}{\eta}} + \gamma^{\frac{1}{\eta}} C_{f,t}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{B.19}$$

where γ is the imports share, taking values [0,1], and $\eta > 0$ measuring the intertemporal elasticity of substitution between domestic and foreign imported goods. Households allocate their expenditures optimally between these goods according to the demand function of each category of good as:

[61] Koop and Korobilis (2012) argue that iterated forecasts with DMA-DMS models require predictive simulations, which given the large number of predictors, will make this task computationally infeasible. Nevertheless, Wright (2008) shows that BMA models deliver similar results under both methods.

$$C_{h,t} = (1-\gamma)\left[\frac{P_{h,t}}{P_t}\right]^{-\eta} C_t \qquad \text{and} \qquad C_{f,t} = \gamma\left[\frac{P_{f,t}}{P_t}\right]^{-\eta} C_t \tag{B.20}$$

where $P_{h,t}$ and $P_{f,t}$ are the prices for the home and imported products respectively, while the consumer price index P_t is given by:

$$P_t = \left[(1-\gamma)P_{h,t}^{1-\eta} + \gamma P_{f,t}^{1-\eta}\right]^{\frac{1}{1-\eta}} . \tag{B.21}$$

Monopolistically competitive households, supply the economy-wide labour market, while the labour demand function is given by:

$$N_t(i) = \left[\frac{W_t(i)}{W_t}\right]^{-\Xi} N_t \tag{B.22}$$

where Ξ is the labour demand elasticity and greater than one and constant across workers, while N_t is the per capita employment. Index W_t is the aggregate wage index given by:

$$W_t = \left[\int_0^1 W_t(i)^{1-\Xi} di\right]^{\frac{1}{1-\Xi}} . \tag{B.23}$$

Each household in every period maximises the following utility function:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{(C_t - H_t)^{1-\sigma}}{1-\sigma} - \frac{N_t(i)^{1+\theta}}{1+\theta}\right] \tag{B.24}$$

where β is the discount factor, H_t is the external habit formation assuming that consumption in every period is affected by the previous period consumption and given by $H_t = \zeta C_{t-1}$, σ is the inverse elasticity of intertemporal substitution, and θ denotes the labour supply elasticity. Optimisation is obtained subject to the period budget constraint:

$$P_{h,t}C_{h,t} + P_{f,t}C_{f,t} + E_t\left\{Q_{t,t+1} D_{t+1}\right\} \le D_t + W_t N_t , \tag{B.25}$$

where D_{t+1} is the portfolio of assets maturing in a period ahead, $Q_{t,t+1}$ is the discount factor and W_t is the wage offered for the labour services. Maximising the utility function subject to the budget constraint, the standard consumption Euler equation is obtained:

$$Q_{t,t+1} = \beta E_t \left\{ \frac{U_{c,t+1}}{U_{c,t}} \frac{P_t}{P_{t+1}} \right\}, \tag{B.26}$$

where $U_{c,t} = (C_t - \zeta C_{t-1})^{-\sigma}$. Following Smets and Wouters (2007), $Q_{t,t+1} = (\mu_t^d I_t)^{-1}$ where μ_t^d is the households' assets risk premium and I_t is the assets' nominal rate of return. Steinbach et al. (2009) derive the optimal wage-setting rule by assuming: i) workers have the right to set their wages in a Calvo (1983) style, where θ_w represents those who do not reset their wage (Erceg et al., 2000); ii) those who do not eventually reset their wage in the current period can index it to the previous period's price inflation Π_{t-1} (Rabanal and Rubio-Ramirez, 2005). Hence, they derive the f.o.c. for the labour supply of the households as:

$$E_t \sum_{k=0}^{\infty} (\beta\theta_w)^k \left\{ \left[\frac{\tilde{W}_t}{P_{t+k}} \Pi_{t+k-1}^{\phi_w} (C_{t+k} - H_{t+k})^{-\sigma} - (1+\mu^w) N_{t+k}^{\theta} \right] N_{t+k} \right\} = 0, \tag{B.27}$$

where $\tilde{W}_t$ is the optimal reset wage, ϕ_w controls the indexation degree to the lagged inflation, and $(1+\mu^w)$ is the wage mark-up. Hence combining equation (B.27) with (B.23) and applying the law of large numbers, they obtain:

$$W_t = \left[\theta_w (W_{t-1} \Pi_{t-1}^{\phi_w})^{1-\Xi} + (1-\theta_w) \tilde{W}_t^{1-\Xi} \right]^{\frac{1}{1-\Xi}}. \tag{B.28}$$

Steinbach et al. (2009) describe the domestic production process in two stages. The first stage assumes monopolistically competitive firms indexed by j where $j \in [0,1]$ producing intermediate differentiated goods and setting prices in a Calvo-style (Gali and Monacelli, 2005). At the second stage, the perfectly competitive final producer will combine the differentiated goods and produce the final good.

Intermediate goods producers, technology and price

Each domestic firm produces $Y_t(j)$ goods with a production function:

$$Y_t(j) = Z_t N_t(j) \qquad \text{(B.29)}$$

where $z_t = \log(Z_t)$ and follows an AR(1) process. The labour input for each *j* firm is given by the composite function:

$$N_t(j) = \left[\int_0^1 N_t(i)^{1-\frac{1}{\Xi}} di \right]^{\frac{\Xi}{\Xi-1}}, \qquad \text{(B.30)}$$

and the total nominal cost function:

$$TC_t^n = W_t N_t(j). \qquad \text{(B.31)}$$

Combining eq. (B.31) with eq. (B.29) yields the marginal cost function in terms of real wages, as:

$$MC_t = \frac{W}{Z_t P_{h,t}}. \qquad \text{(B.32)}$$

As mentioned earlier, intermediate firms set their prices as in Calvo (1983) with θ_h as the probability for each firm that does not reset its price. In addition, it is assumed that prices for the home country are indexed to the last period's inflation (Smets and Wouters, 2002). According to Justiniano and Preston (2010), firms will select the optimal reset price $\widetilde{P}_{h,t}$ by solving their profit maximisation problem given by the following expected present discounted profits:

$$E_t \sum_{k=0}^{\infty} \theta_h^k Q_{t,t+k} Y_{t+k}(j) \left[\widetilde{P}_{h,t} \Pi_{h,t+k-1}^{\phi_h} - MC_{t+k} P_{h,t+k} \right], \qquad \text{(B.33)}$$

subject to the demand curve for intermediate goods:

$$Y_t(j) = \left[\frac{P_{h,t}(j) \Pi_{h,t-1}^{\phi_h}}{P_{h,t}} \right]^{-\xi_h} Y_t, \qquad \text{(B.34)}$$

where ϕ_h is the indexation degree to the past inflation and Y_t is the market clearing condition. Thus, maximising eq. (B.33) implies the f.o.c.:

$$E_t \sum_{k=0}^{\infty} \theta_h^k Q_{t,t+k} Y_{t+k}(j) \left[\tilde{P}_{h,t} \Pi_{h,t+k-1}^{\phi_h} - \left(1+\mu^p\right) MC_{t+k} P_{h,t+k} \right] = 0 , \qquad \text{(B.35)}$$

where profits are maximised by setting the optimal reset $\tilde{P}_{h,t}$ equal to a mark-up μ^p over the expected MC_{t+k}.

Final goods producers and prices

Producers use the intermediate goods as input and compose the final goods, while their technology production function is given by:

$$Y_t = \left[\int_0^1 Y_t(j)^{\frac{\xi_h - 1}{\xi_h}} dj \right]^{\frac{\xi_h}{\xi_h - 1}} , \qquad \text{(B.36)}$$

and the price index:

$$P_{h,t} = \left[\int_0^1 P_{h,t}(j)^{1-\xi_h} dj \right]^{\frac{1}{1-\xi_h}} . \qquad \text{(B.37)}$$

Bringing the Calvo-style price setting and the price indexation behaviour into equation (B.37), the following aggregate price index is derived as in Justiniano and Preston (2010):

$$P_{h,t} = \left[\theta_h (P_{h,t-1} \Pi_{h,t-1}^{\phi_h})^{1-\xi_w} + (1-\theta_h) \tilde{P}_{h,t}^{1-\xi_h} \right]^{\frac{1}{1-\xi_h}} , \qquad \text{(B.38)}$$

where $\tilde{P}_{h,t}$ is the optimal reset price.

International trade and incomplete exchange rate pass-through

As discussed and explained before, the existence of a deviation from the law of one price (l.o.p.) in the short-run and the achievement of the complete exchange rate pass-through in the long-run can be assumed and remains to model it. Hence, the deviation from the (l.o.p.) is defined by:

$$\Psi_{f,t} = \varepsilon_t \frac{P_t^*}{P_{f,t}}, \tag{B.39}$$

where $\Psi_{f,t}$ captures the deviation, ε_t is the current nominal exchange rate (home price for a unit of a foreign currency), P_t^* is the world-market price and $P_{f,t}$ is the price of imported goods in the home currency. Similarly, the importing retailers now face their own profit maximisation problem and need to find the optimal price $\tilde{P}_{f,t}(j)$, assuming a Calvo-type behaviour once again. They seek to maximise the following objective:

$$E_t \sum_{k=0}^{\infty} (\theta_f \beta)^k Q_{t,t+k} C_{f,t+k}(j) \left[\tilde{P}_{f,t}(j) - \varepsilon_{t+k} P_{t+k}^*\right], \tag{B.40}$$

subject to the demand curve that they face: $$C_{f,t}(j) = \left[\frac{\tilde{P}_{f,t}(j)}{P_{f,t}}\right]^{-\xi_f} C_{f,t}. \tag{B.41}$$

Hence, the optimal solution to their problem is given by the f.o.c.:

$$E_t \sum_{k=0}^{\infty} (\theta_f \beta)^k C_{f,t+k} Q_{t,t+k} \left[\tilde{P}_{f,t}(j) - (1+\mu^f)\varepsilon_{t+k} P_{t+k}^*\right] = 0. \tag{B.42}$$

So, the local importing retailer sets his optimal price of the imports equal to a mark-up μ^f over the expected world price in terms of the home currency. The price index for the imported goods taking into account the price-setting behaviour:

$$P_{f,t} = \left[\int_0^1 P_{f,t}(j)^{1-\xi_f} dj\right]^{\frac{1}{1-\xi_f}}, \tag{B.43}$$

and applying the law of large numbers the overall price index:

$$P_{f,t} = \left[\theta_f P_{f,t-1}^{1-\xi_f} + (1-\theta_f)\tilde{P}_{f,t}^{1-\xi_f}\right]^{\frac{1}{1-\xi_f}}. \tag{B.44}$$

Note that retailers who do not reset their prices do not index them to the lagged inflation as well. Next the terms of trade and the real exchange rate are defined respectively as:

$$S_t = \frac{P_{f,t}}{P_{h,t}} \quad \text{and} \quad Q_t = \varepsilon_t \frac{P_t^*}{P_t}. \qquad \text{(B.45a, B.45b)}$$

The goods market clearing conditions implies: $Y_t = C_{h,t} + C_{h,t}^*$ where $C_{h,t}^*$ denotes the exports of the domestically produced goods. The UIP condition for the nominal interest rates is given by a log-linearised version as in Adolfson et al. (2008), with the risk premium components capturing the forward premium puzzle as discussed in the main text. A complete DSGE model requires the monetary policy behaviour to be specified, which is assumed to follow a forward-looking Taylor rule, as presented in eq. (3.28).

DSGE estimation

Following the recent literature, we use Bayesian methods with prior assumptions from the literature and allowing for the data likelihood to estimate the parameters of the DSGE system. Many empirical works of the last decade have focused on this kind of method, (see, e.g. Smets and Wouters, 2004; An and Schorfheide, 2007a,b; Justiniano and Preston, 2010; Marcellino and Rychalovska, 2014), taking the observed data as given and treating the unknown parameters as random variables. Following Villemot (2011), the linear rational expectations model can be written as:

$$E_t\{f(y_{t+1}, y_t, y_{t-1}, u_t)\} = 0 \qquad \text{(B.46)}$$

$$A(E_t y_{t+1}) + By_t + Gy_{t-1} + u_t = 0 \qquad \text{(B.47)}$$

where y_t is the vector of our endogenous variables, $u_t \sim i.i.d.\, N(0, H)$ collects all the exogenous stochastic shocks, and *A*, *B* and *G* collect all the deep parameters of the DSGE system. We can also define the vector Ψ, which contains all the parameters and shocks (*A*, *B*, *G* and *H*). The solution to the system is given by the policy function, using the Blanchard and Kahn (1980) method, which relates the current state of the variables with the past state and the current shocks, such as:

$$\hat{y}_t = R\hat{y}_{t-1} + Qu \qquad \text{(B.48)}$$

Eq. (B.48) can be used as the transition equation while the measurement one can take the following form:

$$y_t^* = M\bar{y} + M\hat{y}_t + \varepsilon_t \qquad \text{(B.49)}$$

where y_t^* are the observables, $\bar{y}$ is the steady state vector, $\hat{y}$ is a vector containing the deviations of the variables from their steady state and ε_t is an error term. Both equations (B.48) and (B.49) represent the state space form of the DSGE model and the likelihood function can be obtained using the Kalman filter. The posterior kernel of the structural parameters can be obtained by combining the likelihood function with the prior distributions. Still, the posterior is non-linear and a complicated density, in which achieving our goal requires an MCMC simulation method such as the Metropolis-Hasting algorithm. For this empirical work, we use the Dynare version 4.4.3 software, which implements the above estimation procedure.[62] Regarding the priors (Table B1), we use those used by Smets and Wouters (2007) and Justiniano and Preston (2010). We calibrate only three parameters, the discount factor β, which is set equal to 0.99, implying a 4% riskless annual interest rate at the steady state, γ equal to 0.10, which is the average imports-to-GDP ratio over our sample period for the U.S., and Ξ equal to 6 as in Alpanda et al. (2011).[63]

[62] For more detail, see the manual (Adjemian *et al.*, 2011) at the following link: http://www.dynare.org/documentation-and-support ; and An and Schorfheide (2007a).

[63] I would like to thank Dr. Sami Alpanda for sharing Alpanda et al.'s (2011) Dynare code.

Table B.1: Prior selection and estimated posterior means of the DSGE parameters

Structural Parameters	**Prior density**	**Posterior mean**
ζ Habit in consumption	B (0.7 , 0.15)	0.5861
σ Inverse of intertemporal substitution elasticity	G (1.5 , 0.37)	1.5507
θ Inverse of labour supply elasticity	G (2 , 0.75)	1.5576
η Substitution elasticity between home and foreign	G (1.5 , 0.75)	1.0084
χ Debt elasticity of risk premium	N (0.01 , 0.001)	0.0103
φ UIP parameter	B (0.1 , 0.2)	0.0240
θ_h Calvo probability: home good price	B (0.5 , 0.15)	0.9069
θ_f Calvo probability: foreign good price	B (0.5 , 0.15)	0.4942
θ_w Calvo probability: wage	B (0.5 , 0.15)	0.6308
φ_h Indexation: home good price	B (0.7 , 0.15)	0.6793
φ_f Indexation: foreign good price	B (0.7 , 0.15)	0.5414
φ_w Indexation: wage	B (0.7 , 0.15)	0.8194
ρ Taylor rules: smoothing	B (0.7 , 0.15)	0.6288
λ_π Taylor rule: inflation	G (0.5 , 0.25)	1.7135
λ_y Taylor rule: output growth	G (0.25 , 0.1)	0.1542
λ_d Taylor rule: depreciation	G (0.12 , 0.05)	0.1997

Persistence parameters	**Prior density**	**Posterior mean**
Productivity shock	B (0.5 , 0.2)	0.9242
Consumption demand shock	B (0.5 , 0.2)	0.8110
Home good cost-push shock	B (0.5 , 0.2)	0.0224
Foreign good cost-push shock	B (0.5 , 0.2)	0.8988
Wage cost push shock	B (0.5 , 0.2)	0.7250
Depreciation shock	B (0.5 , 0.2)	0.4425
Monetary policy shock	B (0.5 , 0.2)	0.3503
Foreign output shock	B (0.5 , 0.2)	0.7120
Foreign inflation shock	B (0.5 , 0.2)	0.7331
Foreign interest rate shock	B (0.5 , 0.2)	0.3979

Standard deviations of shocks	**Prior density**	**Posterior mean**
Productivity shock	IG (0.5%, inf)	0.73 %
Consumption demand shock	IG (0.5%, inf)	0.24 %
Home good cost-push shock	IG (0.5%, inf)	0.21 %
Foreign good cost-push shock	IG (0.5%, inf)	5.45 %
Wage cost push shock	IG (0.5%, inf)	0.30 %
Depreciation shock	IG (0.5%, inf)	0.40 %
Monetary policy shock	IG (0.5%, inf)	1.06 %
Foreign output shock	IG (0.5%, inf)	1.09 %
Foreign inflation shock	IG (0.5%, inf)	0.92 %
Foreign interest rate shock	IG (0.5%, inf)	2.03 %

Notes: Posterior estimates come from the last recursive estimation, using the most recent vintage of our dataset. Also, priors are mainly from Smets and Wouters (2007). Also, B: beta, G: gamma, N: normal and IG: inverse gamma distribution.

Table B.2: Data transformation for the DMA and DMS analysis

	Macroeconomic variables	*Transformation code*
1.	1-month forward (USD/GBP) exchange rate premium	1
2.	3-month forward (USD/GBP) exchange rate premium	1
3.	6-month forward (USD/GBP) exchange rate premium	1
4.	12-month forward (USD/GBP) exchange rate premium	1
5.	U.S. real GDP (seasonally adjusted)	2
6.	U.K. real GDP (seasonally adjusted)	2
7.	U.S. output gap (HP-filtered)	1
8.	U.K. output gap (HP-filtered)	1
9.	U.S. money supply (M1)	2
10.	U.K. money supply (M4)	2
11.	Real (USD/GBP) exchange rate	2
12.	U.S. price Inflation (annualised)	1
13.	U.K. price Inflation (annualised)	1
14.	U.S. 10-year maturity government bond rates	1
15.	U.K. 10-year maturity government bond rates	1

Notes: Transformation codes are as follow: (1)-variable in logarithm, (2)-first difference of the variable in logarithm.

Table B.3: Clark and West (2006) test statistics of Tables 3.1 – 3.7

	Δs_t	FPTS	UIP	PPP	Monetary	Taylor rule
BVAR(1)	*t+1*	1.282	0.384	1.490	0.936	1.687
	t+2	-1.136	-1.463	0.919	0.699	1.411
	t+3	-0.662	-0.988	1.146	1.647	0.691
Homoscedastic TVP-BVAR(1)	*t+1*	1.131	0.118	0.882	0.654	2.048
	t+2	-1.669	-1.318	-0.807	-0.009	0.195
	t+3	-1.011	-1.006	-1.622	-1.336	-1.329
Heteroscedastic TVP-BVAR(1)	*t+1*	1.282	0.250	1.292	0.620	2.116
	t+2	-1.009	-1.551	0.246	-0.783	-0.725
	t+3	-1.321	-1.235	0.736	-1.044	0.466

	Δs_t	15 Major Predictors
DMA	*t+1*	1.281
	t+2	-1.122
	t+3	-2.086

	Δs_t	15 Major Predictors
DMS	*t+1*	1.692
	t+2	0.253
	t+3	-1.327

	Δs_t	
DSGE	*t+1*	-0.476
	t+2	0.349
	t+3	0.286

<u>*Sensitivity Analysis*</u>

	Δs_t	FPTS	UIP	PPP	Monetary	Taylor rule
Homoscedastic TVP-BVAR(1)	*t+1*	0.473	-0.091	1.285	1.469	2.275
	t+2	-1.130	-1.251	0.053	0.173	0.577
	t+3	-1.864	-1.320	-0.869	-0.912	0.141
Heteroscedastic TVP-BVAR(1)	*t+1*	0.578	-0.850	1.706	1.832	1.542
	t+2	-1.053	-1.285	1.907	-0.825	-0.519
	t+3	-1.093	-1.123	0.837	1.028	1.149

Notes: Tables report the one-sided Clark and West (2006) test statistics of the out-of-sample results of the third chapter.

Appendix C

Forward exchange rate jumps under disaster (Brexit) conditions

In this section, we develop a model, analysing the behaviour of the forward USD/GBP exchange rates and their potential jumps at periods when the corresponding expected spot rates include the referendum result of Brexit polls, reflecting the probabilities of *leave* or *stay*. We start our analysis assuming that the current spot exchange rate depends on the expectations about the future value of the spot rate and the current value of the fundamentals. This model takes the form of a *linear expectational difference equation of first order*. So, a simple fundamentals-based exchange rate model may take the form:

$$s_t = a + bx_t + cE_t(s_{t+1}), \tag{C.1}$$

or

$$E_t(s_{t+n}) = a + bE_t(x_{t+n}) + cE_t(s_{t+n+1}) \tag{C.2}$$

where x_t is a set of the observed fundamentals at time *t*, s_t the natural log of the spot exchange rates and $E_t s_{t+1}$ the one-period ahead expected spot rate, given all the available information until time *t*. Also, by using the method of repeated forward substitutions for *n*-periods ahead and the law of iterated expectations, eq. C.1 becomes:

$$s_t = a\left(1 + c + c^2 + \ldots + c^n\right) + bx_t + b\sum_{i=1}^{n} c^i E_t(x_{t+i}) + c^{n+1}E_t(s_{t+n+1}). \tag{C.3}$$

Also, taking the conditional expectations on both sides and forward it a period-ahead:

$$E_t s_{t+1} = a\left(1 + c + c^2 + \ldots + c^n\right) + bE_t(x_{t+1}) + b\sum_{i=1}^{n} c^i E_t(x_{t+i+1}) + c^{n+1}E_t(s_{t+n+2}). \tag{C.4}$$

Moving to the forward rates analysis, the theoretical basis is given by Fama (1984). He states that if f_t is the natural logarithm of the forward rate observed at time *t* for delivering *n* periods ahead, s_t is the natural logarithm of the spot exchange rate, and assuming risk aversion, then:

$$f_t = E_t(s_{t+n}) + rp_t, \tag{C.5}$$

where, $E_t(s_{t+n})$ is the expected spot rate at *n*-periods ahead conditional on the information set up to time *t*, and rp_t is the time-varying forward risk premium. Fama (1984) describes the forward rate as the *market determined certainty equivalent of the future spot rate*, while Barkoulas et al. (2003) state that, if agents are assumed rational, then a risk premium is due to a demanded compensation above the expected spot depreciation rate for holding the forward contract.

Turning to the Brexit case, if *L* denotes the Brexit scenario, *S* the Bremain scenario, q_t the time-varying probability of leaving and $(1-q_t)$ the probability of remaining in the E.U., then the 1-month forward exchange rate observed on 19 May 2016 for delivering one day before the final result is announced, (23 June 2016) is given by:

$$f_{t-1} = E_t\left(s_{t+n-1}^S\right) + rp_{t-1}^S = a + bE_t\left(x_{t+n-1}^S\right) + cE_t\left(s_{t+n}^S\right) - rp_{t-1}^s \ , \qquad \text{(C.6)}$$

where *t+n* corresponds to the day that the referendum final result is officially announced (24 June 2016). This analysis considers the 1-month forward rate for convenience, but is also applicable in forward rates of any maturity. The forward exchange rate observed on 20 May 2016 maturing at the day the result is announced is given by:

$$f_t = q_t\left[E_t\left(s_{t+n}^L\right) + rp_t^L\right] + \left(1 - q_t\right)\left[E_t\left(s_{t+n}^S\right) + rp_t^S\right] \ =$$

$$= q_t\left[a + bE_t x_{t+n}^L + cE_t s_{t+n+1}^L + rp_t^L\right] + \left(1 - q_t\right)\left[a + bE_t x_{t+n}^S + cE_t s_{t+n+1}^S + rp_t^S\right] \ \text{(C.7)}$$

In this case, the forward exchange rate is determined as the weighted average of the expected future fundamentals and spot rate, reflecting both potential outcomes. Also, rp_t^L represents the time-varying disaster risk premium and rp_t^S the stay risk premium. We consider the Brexit case as a disaster, given the analysis published by U.K. Parliament H.M. Treasury (2016a, 2016b) and Dhingra et al. (2016) predicting a per capita GDP loss of up to 9.5% in the long run under the worst-case scenario. The 1-month forward exchange rate observed on 23 May 2016 and maturing one business day after the result announcement (27 June 2016) is given by:

$$f_{t+1} = q_{t+1}\left[E_t\left(s_{t+n+1}^L\right) + rp_{t+1}^L\right] + \left(1 - q_{t+1}\right)\left[E_t\left(s_{t+n+1}^S\right) + rp_{t+1}^S\right] \ =$$

$$= q_{t+1}\left[a + bE_t x_{t+n+1}^L + cE_t s_{t+n+2}^L + rp_{t+1}^L\right] + \left(1 - q_{t+1}\right)\left[a + bE_t x_{t+n+1}^S + cE_t s_{t+n+2}^S + rp_{t+1}^S\right] \ \text{(C.8)}$$

We now turn to measuring the changes of the forward rates during these delivering dates. First, we compute the $f_t - f_{t-1}$ difference:

$$f_t - f_{t-1} = q_t\left[bE_t x_{t+n}^L - bE_t x_{t+n}^S + cE_t s_{t+n+1}^L - cE_t s_{t+n+1}^S + rp_t^L - rp_t^S\right] +$$

$$+ bE_t x_{t+n}^S - bE_t x_{t+n-1}^S + cE_t s_{t+n+1}^S - cE_t s_{t+n}^S + rp_t^S + rp_{t-1}^S \qquad \text{(C.9)}$$

In this case, the jump is driven, among others, by the news about fundamentals before and after the result, the expected spot rate after the result and the probability of leaving. If the news about fundamentals prior to leaving are weak then changes mostly driven by changes in probabilities of leaving. Also, the risk premium differential $rp_t^L - rp_t^S$ should be large given the high disaster probability (23%) of Brexit, at time t [64]. Turning to the $f_{t+1} - f_t$ differential:

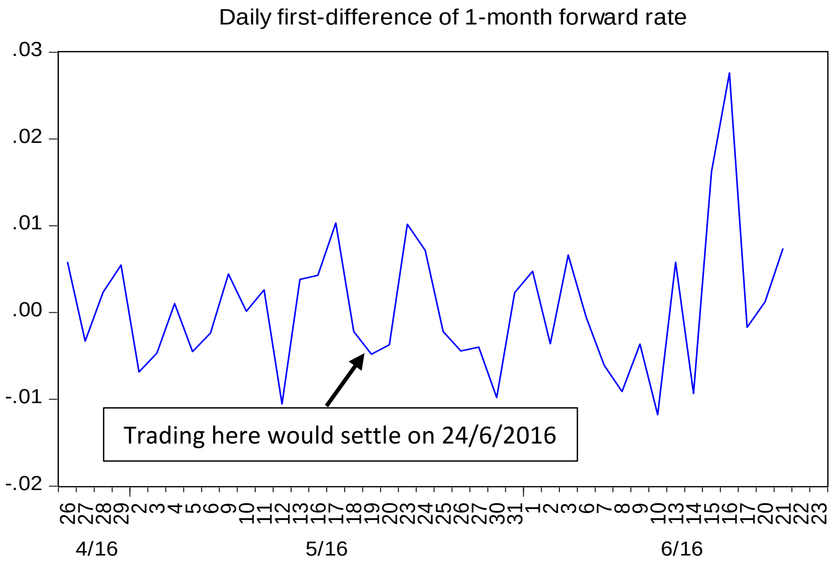
$$f_{t+1} - f_t = q_{t+1}\left[bE_t x_{t+n+1}^L - bE_t x_{t+n+1}^S + cE_t s_{t+n+2}^L - cE_t s_{t+n+2}^S + rp_{t+1}^L - rp_{t+1}^S\right] +$$

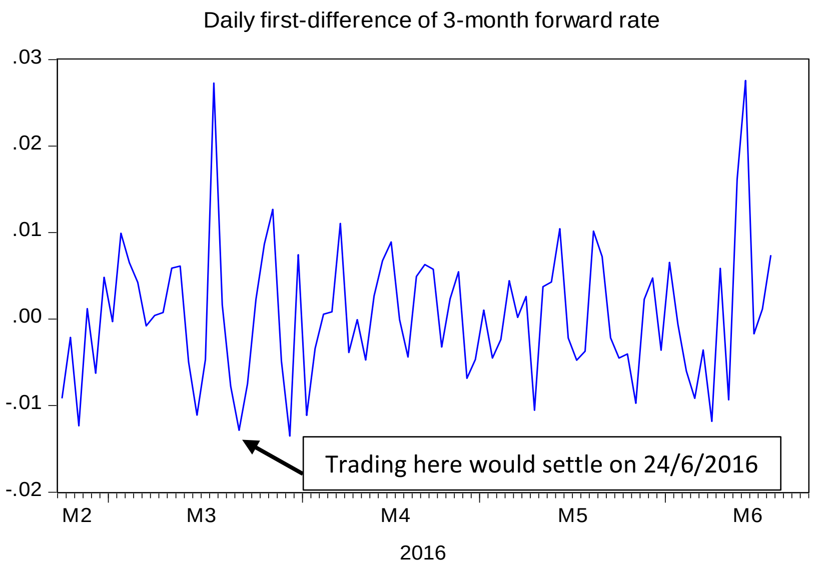
$$+ q_t\left[-bE_t x_{t+n}^L + bE_t x_{t+n}^S - cE_t s_{t+n+1}^L + cE_t s_{t+n+1}^S + rp_t^S - rp_t^L\right] +$$

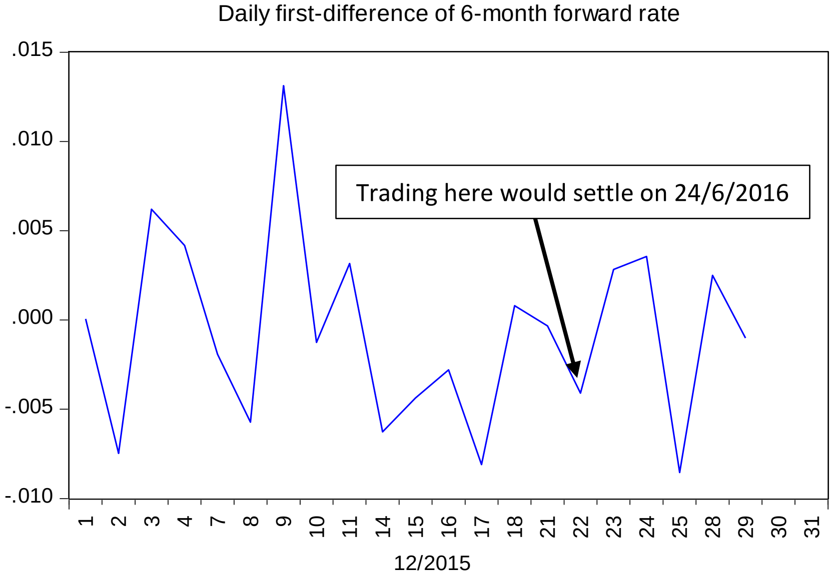
$$+ bE_t x_{t+n+1}^S - bE_t x_{t+n}^S + cE_t s_{t+n+2}^S - cE_t s_{t+n+1}^S + rp_{t+1}^S - rp_t^S . \qquad \text{(C.10)}$$

The analysis of this jump is more complicated as it depends a lot on the probabilities or the change of the probabilities and the news about the fundamentals. This is worth investigating in a future research. However, there should be noticeable jump for the forward rates that include the referendum outcome, given the Brexit probability and the potential disasters this may cause. Also, we should mention that the behaviour of the forward rates after the referendum outcome, may be driven by the news about negotiations with the E.U. Below, we show the graphs of the first-difference of the 1-, 3-, 6- and 12-month USD/GBP forward rates (in natural logarithms), looking for potential jumps on the first day the log-change includes the outcome of the referendum.

[64] The bookmakers' odds can be used as a proxy for the probabilities of *leave* and *remain*, and can be found at: https://blogs.spectator.co.uk/2016/05/a-bookies-perspective-on-brexit-and-a-tip-for-what-to-bet-on/ .


Daily first-difference of 1-month forward rate
.03
.02
.01
.00
-.01
-.02
Trading here would settle on 24/6/2016
4/16
5/16
6/16


Daily first-difference of 3-month forward rate
.03
.02
.01
.00
-.01
-.02
Trading here would settle on 24/6/2016
M2
M3
M4
M5
M6
2016



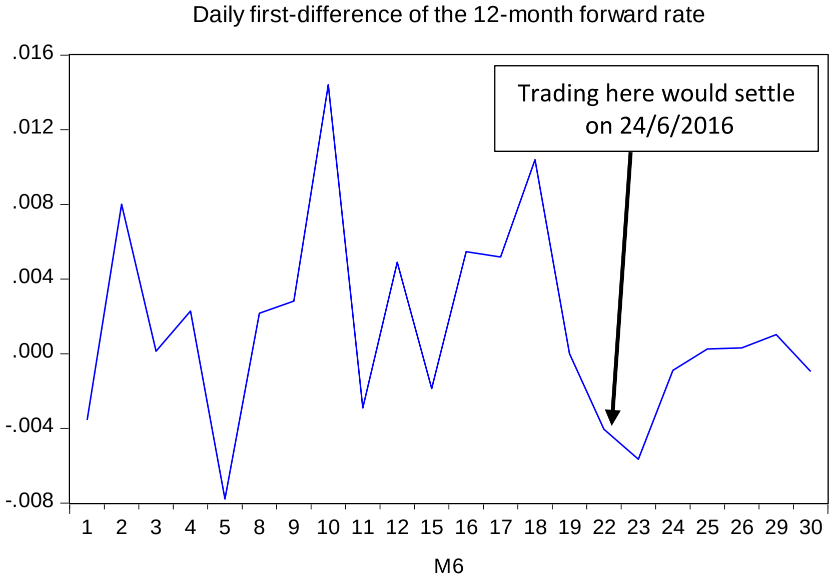


Figure C.1: Graphs show the first-difference of the 1-, 3-, 6- and 12-month USD/GBP forward rates in natural logarithms

It is graphically obvious that, more or less, all of the forward rate changes drop when settlement spans the result announcement date. However, the jump is more visible in the 3-month and 12-month forward rate graphs.

Table C.1: Clark and West (2006) test statistics of Table 4.6

Fama-based models	*w/o FPCs*	*Start*	*During*	*End*
t+1	0.087	0.196	0.502	0.267
t+2	-1.991	-1.806	-0.629	-2.064
t+3	-1.618	-1.663	-1.225	-1.692
t+4	0.679	0.599	-0.994	0.488
PPP-based model				
t+1	0.610	0.730	1.236	0.737
t+2	-1.182	-1.009	-0.062	-1.203
t+3	-0.870	-0.974	-0.251	-0.868
t+4	-0.612	-0.643	-0.912	-0.634
Monetary-based model				
t+1	0.505	0.494	1.475	0.618
t+2	0.301	0.287	1.317	0.199
t+3	0.732	0.508	0.925	0.714
t+4	0.819	0.758	0.260	0.823
Taylor-rule model				
t+1	1.072	0.991	1.742	1.138
t+2	0.569	0.578	1.284	0.613
t+3	0.707	0.743	0.946	0.685
t+4	0.457	0.516	-0.741	0.505

Notes: Tables report the one-sided Clark and West (2006) test statistics of the out-of-sample results of the forth chapter.

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