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One model or many? Exchange rates determinants and their predictive capabilities.

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One model or many? Exchange rates determinants and their predictive capabilities.

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Abstract

In this paper the Dynamic Bayesian Model Averaging (DMA) algorithm is used to establish the key determinants of the nominal exchange rates of 5 currencies: CAD, EUR, GBP, CHF and JPY against the US dollar. My results indicate that the importance of the variables in the exchange rate forecasting can substantially differ in time. Even among the set of developed countries, there are visible differences in the set of key determinants of the exchange rate. However, the lagged value of the exchange rate remains always an important variable indicating significant persistence in the exchange rate time series. Furthermore, the PPP rate, Terms of Trade (TOT) and output per worker are also variables that have high Posterior Inclusion Probabilities among the analysed countries. My results show that macroeconomic fundamentals are not leading indicators of the exchange rates. As a result, to outperform the random walk (naive) forecast of the exchange rate using the macroeconomic fundamentals, a good quality of the forecast of the explanatory variables is required.

Keywords: Exchange rates, forecasting, Bayesian Model Averaging

JEL: C11, C33, F14, F15

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1 Introduction

Even though economic literature has long been discussing the relation between macroeconomic fundamentals and exchange rates, there is no consensus on which theories (models) and variables are the crucial determinants of the exchange rate movements. Early studies such as the Meese and Rogoff (1983) argued that the random walk model outperforms all structural models, however many authors later show that it is possible to beat the random walk (see Rossi, 2013, for a discussion). In a recent study, Cheung et al. (2019) provide an extensive study of economic literature and compare eight models against the random walk. The authors, however, state that their primary goal is not to determine which model provides best forecasts, but rather to establish *which model provides greatest empirical content*. As a result, the authors conduct simulations where they assume knowledge of the realised values exchange rate determinants that allow for historical decomposition of the exchange rate movements.

In my study, I put more emphasis on the forecasting capabilities of the macroeconomic variables and use a different method - Dynamic Bayesian Model Averaging (DMA). In general, model averaging procedures gained substantial popularity in the economic literature, especially in the case of various forms of Bayesian model averaging, that began its expansion from the literature on the economic growth (see, e.g. Sala-I-Martin et al., 2004; Ley and Steel, 2009; Eicher et al., 2011; Amini and Parmeter, 2012) and followed by analyses focusing on current account imbalances (e.g. Ca'Zorzi et al., 2012; Moral-Benito and Roehn, 2016; Dybka and Rubaszek, 2017), trade performance (e.g. Bierut and Dybka, 2019) or even shadow economy estimation (e.g. Dybka et al., 2020). In the context of forecasting, there are various studies using both static and dynamic variants of Bayesian Model Averaging that include, among others, (e.g. Koop and Korobilis, 2012; Bork and Møller, 2015; Wang et al., 2016; Montero-Manso et al., 2020).

The DMA procedure has some essential advantages that constitute a substantial contribution of my study. First, DMA allows me to combine all the potential determinants of the exchange rate into one framework. The obtained Posterior Inclusion Probabilities (PIP) can be interpreted as a measure of empirical importance of the given variable, thus providing insights on the identification of fundamental macroeconomic determinants of the nominal exchange rate movements. Second, the dynamic version of the algorithm allows for changes in the PIPs and the coefficients in time. This way, I can verify to what extent the importance of macroeconomic determinants of exchange rates changes over time. Third, I also study the forecasting capabilities under different scenarios regarding the knowledge of the realized values of macroeconomic determinants to establish what conditions must be met so that macroeconomic variables can outperform the random walk.

2 The economic theory

Economic literature contains various theories regarding the key determinants of the exchange rate movements that indicate the existence of different types of mechanisms describing the relationship between the macroeconomic fundamentals and changes in the exchange rate:

- **Relative purchasing power parity (PPP).** Recent studies (see e.g. Ca' Zorzi et al., 2016;

Ca' Zorzi and Rubaszek, 2020; Mijakovic et al., 2020) show that models using the adjustment mechanism of the deviation of the real exchange rate from the PPP can be a very effective predictive tool.

- **Uncovered interest parity (UIP).** According to this theory, the exchange rate should adjust accordingly to the difference in the interest rates between the two countries. This theory alone seems to be insufficient to explain exchange rate movements, however, some studies (see e.g. Chinn and Meredith, 2004) indicate that UIP can be used to for long-term forecasts.

- **Taylor rule fundamentals.** Monetary policy rule proposed by Taylor (1993), can also be used as a substitute for the monetary policy interest rate as in the Molodtsova and Papell (2009).

- **Yield curve slope** that can be approximated using the difference between the three month and ten-year interest rates (see e.g. Chinn and Meredith, 2004; Buncic and Piras, 2016)

- **Economic development.** Early studies, such as Harrod (1933), followed by (Balassa, 1964; Samuelson, 1964), focused on the importance of the economic development on the exchange rate and the relative prices. Based on the Harrod-Balassa-Samuelson theory, one can expect appreciation of the exchange rates of the developing economies.

- **Monetary models.** Another mechanism of exchange rate adjustments was presented in the so-called sticky-price monetary models, developed by (Dornbusch, 1976; Frankel, 1979) that included (apart from the GDP) also money (monetary aggregate), interest and inflation rates. Such models can also be further extended to account for risk and/or liquidity factors (see e.g. Engel and Wu, 2018; Dąbrowski et al., 2018; Cheung et al., 2019). Moreover, Engel and West (2005) showed that it is possible to reconcile macroeconomic fundamentals and exchange rates within the present value model.

- **Behavioral Equilibrium Exchange Rate (BEER) models.** This category of models can be viewed as a way of incorporating several theories into one model. The BEER approach was developed by MacDonald and Clark (1998). In general, BEER models include the following variables interest rates, relative prices, government debt, terms of trade and net foreign assets (see e.g. Roszkowski et al., 2014; Couharde et al., 2018).

- **Macroeconomic balances (MB) approach** developed by Faruqee et al. (1999) and further extended by the IMF in the External Balance Assessment (EBA) framework, that focuses on the balance of the current account. The current account surplus indicates that the exchange rate should appreciate.

- **Cointegration.** Another approach relies on cointegration relation between the macroeconomic fundamentals and the exchange rates as in the Wdowiński (2011), that can be also included in the VAR framework Grabowski and Welfe (2019) or the panel data framework Dąbrowski et al. (2014).

- **Expectations and animal spirits.** Kaltenbrunner (2015); Barbosa et al. (2018) indicate that aggregate expectations also have a profound impact on the exchange rate movements, especially in the case of developing and emerging countries (that can be approximated by yield curve or liquidity premium differential. Chojnowski and Dybka (2017) propose a novel two-step approach. They begin with the estimation of the economic sentiments and then they apply the obtained measure in the VAR framework that offers improved exchange rate forecasting capabilities.

In general, the literature on the relation between the macroeconomic fundamentals and exchange rates is continually growing, and therefore the summary above provides only a brief discussion on different modelling approaches. Nevertheless, it allows the identification of a list of potential exchange rate determinants.

3 Econometric methodology

In my approach, I have divided variables into two categories. In the first category were variables recalculated as the relative measures, where I compared them against the United States economy. In the second category, I have included variables that have already been expressed in relative terms, such as the Terms of Trade.

In my approach, I have used the Dynamic Bayesian Model Averaging (DMA) algorithm. To perform the DMA analysis, I have used the eDMA package, developed by Catania and Nonejad (2018), that is based on the methodology proposed by Raftery et al. (2010); Koop and Korobilis (2012). In the DMA framework, the analysed models are expressed as the Dynamic Linear Processes (DLM) of the following form:

$$FX_t = Y_t^{(j)} \beta_t^{(j)} + \epsilon_t^{(j)},\ \epsilon_t^{(j)} \sim N(0, V_t^{(j)}) \tag{1}$$

where the $Y_t^{(j)T}$ is the vector of predictors included in the model j and the is $\beta_t^{(j)}$ is the vector of time-varying coefficients evolving according to the formula:

$$\beta_t^{(j)} = \beta_{t-1}^{(j)} + \eta_t^{(j)},\ \eta_t^{(j)} \sim N(0, W_t^{(j)}) \tag{2}$$

The changes of the coefficients values depend on the conditional variances: $W_t^{(j)}$ from observational equation (1) and $W_t^{(j)}$ from the state equation (2). In the specific case that $W_t^{(j)} = 0$, the coefficients do not differ in time and we get a static BMA algorithm. Using the DMA framework, however, requires establishing the $W_t^{(j)}$ vector for all the periods. Given that there is 2^K model specifications establishing vector of $W_t^{(j)}$ for each specification seems impossible. To avoid this problem, one can use a forgetting factor, $0 < \delta \leq 1$, that allows controlling the magnitude of shocks to the coefficients by placing weights on the past observations. For example, $delta = 0.99$ means that observations from 20 periods ago receive only 82% of weight as the current observation, whereas $delta = 0.9$ puts weight equal to 12% for observations from 20 periods ago. As a result, the lower the $delta$, the greater the variability of the coefficients. In practice, I have performed the DMA algorithm over a grid of $delta$ from 0.9 to 0.99 that allows estimation of the posterior weighted average value of δ, as proposed by Catania and Nonejad (2018). In addition to δ there is also another forgetting factor for the observational variance

$(V_t^{(j)})$ that I have kept constant and equal to 0.96[1].

The next step of DMA is to compute the posterior probability of model j, $P(M_j|y)$, i.e. the probability of the model conditional on our prior belief, $P(M_j)$, and the marginal likelihood of the model (the probability of the data y conditional on model j), $l(y|M_j)$.

$$P(M_j|Y_t) = \frac{l(y|M_j, Y_{t-1})P(M_j|Y_{t-1})}{\sum_{i=1}^{2^K-1} l(y|M_i, Y_{t-1})P(M_i|Y_{t-1})} \tag{3}$$

As compared to the static BMA approach, the difference lies in the fact that the coefficients can differ in time, as well as the posterior probabilities of the models. In this case, there is third forgetting factor, denoted as α that specifies to what extent probability of the model in time $t-1$ affects the current result, according to the following formula:

$$P(M_j|Y_{t-1}) = \frac{P(M_j|Y_{t-1})^\alpha}{\sum_{i=1}^{2^k-1} P(M_i|Y_{t-1})^\alpha} \tag{4}$$

Throughout my calculations I have tested $\alpha = 0.98$ and $\alpha = 0.96$, but they had limited effect on the obtained results.

4 Potential determinants of the exchange rate movements

Based on the literature review, I have identified 17 potential variables that are likely to affect the exchange rate and as a result, they can be used in forecasting. The complete list of variables, along with their data sources, can be found in Table 1.

Table 1: Potential determinants of the exchange rate movements and their data sources

Variable	**Source**
Exchange rate	IMF IFS
GDP growth rate	IMF WEO; interpolated
GDP per capita (PPP)	IMF WEO; interpolated
Output gap	OECD, IMF; interpolated
Current account balance	IMF (IFS; WEO; interpolation)
M2 money supply	FRED, central bank databases
Inflation CPI	IMF IFS
Composite leading indicator	OECD
General government debt	IMF WEO; interpolated
General government deficit	IMF WEO; interpolated
Output per worker	Own calculations, based on IMF and ILO data
Unemployment rate	ILO
PPP exchange rate	IMF WEO; interpolated

[1]it had little impact on the obtained results.

Terms of trade	IMF IFS
FDI inflow (% of GDP)	IMF WEO; interpolated
Net foreign assets (% of GDP)	Lane and Milesi-Ferretti (2007); interpolated
Monetary policy rate (3 month rate)	Wu-Xia and RBNZ shadow rates; FRED, central bank databases
10 year gov't bond yield	FRED, central bank databases

In this study, I will focus on exchanges rates of five currencies against the US dollar: CAD, EUR, CHF, GBP and JPY over the 1980-2018 period (in the case of CHF sample starts in 1985 and in the case of EUR in 1996). The data used in the analysis had a quarterly frequency.

5 Determinants of the exchange rates movements

In the first part of the analysis, I discuss the crucial determinants of the exchange rates, identified on the basis of Posterior Inclusion Probabilities (PIP). My goal is to establish to what extent the critical determinants of the exchange rates differ among the developed countries, so I analyze each exchange rate separately.

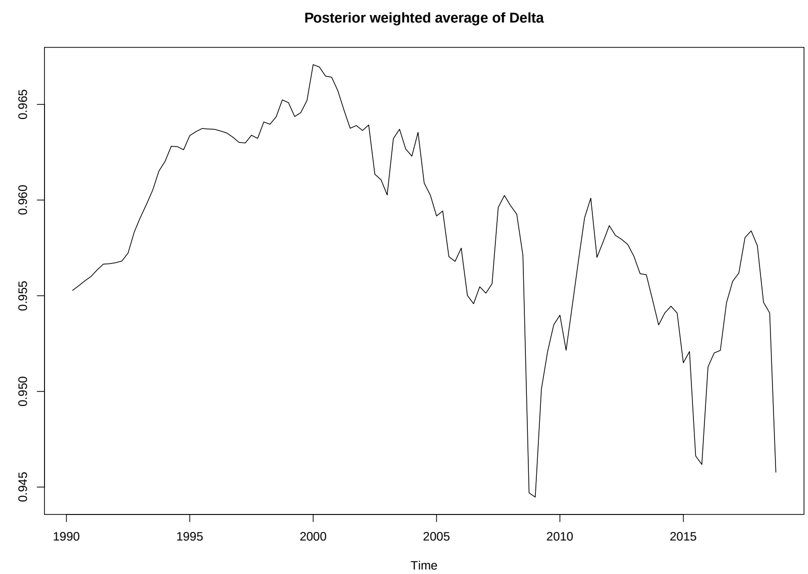
5.0.1 Determinants of the USD/CAD rate

In the case of the USD/CAD rate, the lagged exchange rate retains high PIP over the sample (see Table 2 in the Appendix), indicating that there is significant persistency in the exchange rate. Furthermore, Output per worker, Terms of trade and Purchasing Power Parity remain highly important over the whole sample. In contrast, government deficit, Net Foreign assets (NFA), GDP growth and GDP per capita have increased their Posterior Inclusion probabilities after the year 2000[2].

The obtained values of Posterior Inclusion Probabilities showed significant volatility over the sample, especially over the last 15 years. This result stems from the fact that the posterior weighted value of forgetting factor, δ, has also decreased over the last year, indicating that more flexibility in the parameter's value was allowed. Such a result can be interpreted as evidence that volatility in the CAD/USD market has increased over the last years. What is more, there is a visible drop in the δ value in the periods of the last economic crisis (Great Recession) indicating that some structural changes took place after the crisis.

[2]For the brevity of the discussion I focus only on the 8 variables with highest average PIP over the sample. The charts for the remaining variables are available upon request.

Figure 1: Posterior weighted average estimate of δ (forgetting factor)



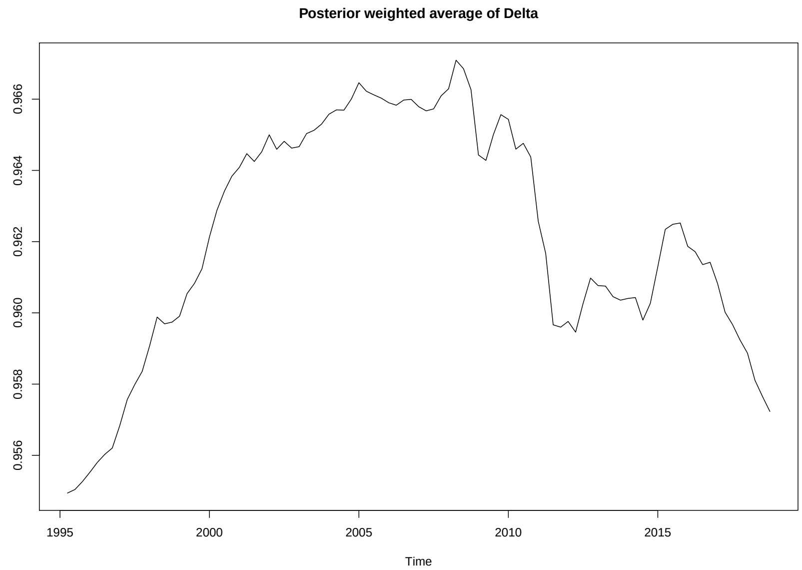
5.0.2 Determinants of the USD/CHF rate

On the one hand, the results obtained in the case of USD/CHF to some extent resemble the Canadian case (see Table 3 in the Appendix). First of all, we can observe that the lagged value of exchange rate, Output per worker and Purchasing Power Parity remain highly important over the whole sample. Second, similar to the Canadian dollar, GDP per capita and Net Foreign Assets also gain importance over time, although in the case of Swiss franc we can observe more gradual growth in the posterior inclusion probability.

On the other hand, there were some essential differences among those countries. Although the PIP of Terms of trade was rather high throughout most of the sample, it seems that it had disappeared in the last three years. Moreover, neither government deficit nor the GDP growth proved to be important in the case of the Swiss franc. In the case of the Swiss franc, the ten-year government bond yield and the inflation rate showed high levels of the posterior inclusion probability over the last 15 years.

In order to better understand the changes in the Swiss franc market, I have presented the values of the forgetting factor, δ, measuring the coefficients volatility. The sample can be divided into two periods. Until 2008, the value of δ was increasing, which means that the coefficient values were stabilizing. However, after the Great Recession, we saw a decrease in the δ value, meaning that the Swiss franc market is less stable after the Great Recession.

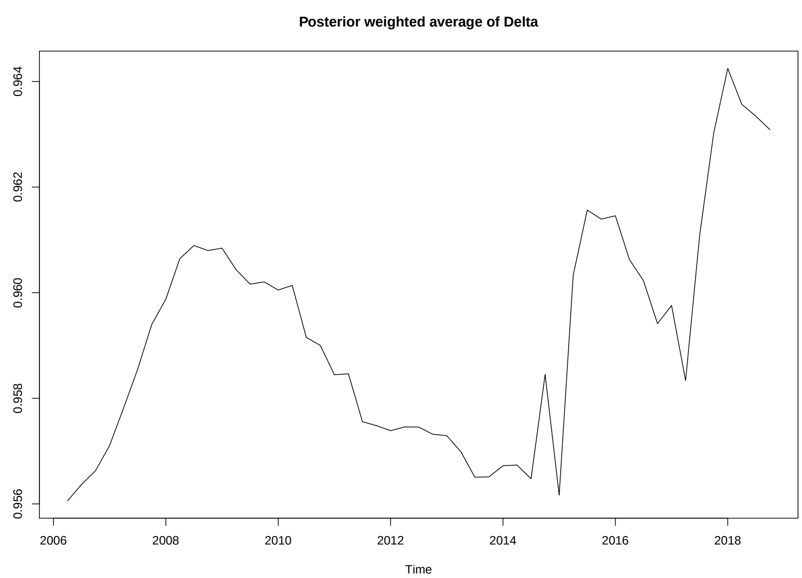
Figure 2: Posterior weighted average estimate of δ (forgetting factor)



5.0.3 Determinants of the EUR/USD rate

In general, the Posterior Inclusion Probabilities obtained in the case of the EUR/USD are similar to CAD and CHF (see Table 4 in the Appendix). The lagged exchange rate, Output per worker, Terms of trade and Purchasing Power Parity remain highly important over the whole sample. After the Great Recession and the European sovereign debt crisis, one can observe that the general government deficit, current account balance and the CPI inflation rate, as well as the GDP per capita, have substantially increased their PIP.

Figure 3: Posterior weighted average estimate of δ (forgetting factor)



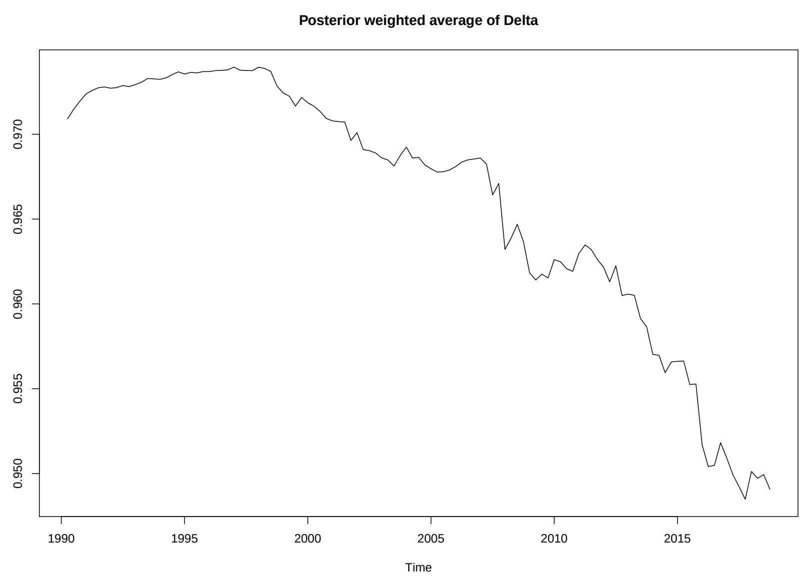
The volatility of the Euro has increased after the Great Recession period, which might be the effect of the sovereign debt problems of several euro area members. It is worth noting that at the end of the sample, the value of δ factor has reached higher levels than before the crisis, indicating stabilization of the EUR/USD market.

5.0.4 Determinants of the USD/JPY rate

Similarly to the Canadian dollar, Swiss franc and Euro, the lagged exchange rate, Output per worker, Terms of trade and Purchasing Power Parity remain highly crucial over the whole sample in the case of Japanese yen (see Table 5 in the Appendix). Interestingly, lagged value of economic sentiments, measured with the Composite Leading Indicator (CLI), increased their importance in recent years.

In the case of the USD/JPY rate, there is significant volatility of the posterior inclusion probabilities. Since the early 2000s, one can observe a steady decrease of the δ factor, that indicates that volatility of the Japanese yen determinants is increasing.

Figure 4: Posterior weighted average estimate of δ (forgetting factor)



5.0.5 Determinants of the USD/GBP rate

The USD/GDP exchange rate seems to differ the most in comparison with the other analyzed currencies (see Table 6 in the Appendix). First of all, the lagged exchange rate does not have the highest Posterior Inclusion Probability, indicating that the persistence of the USD/GBP rate seems less profound than in the case of the remaining analyzed variables.

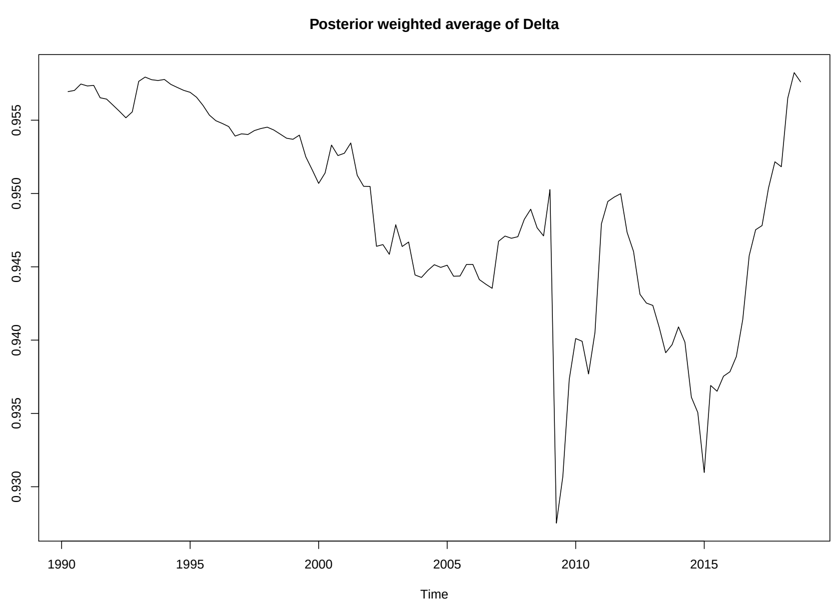
Second, the lagged Composite Leading Indicator is among the top variables with respect to the PIP. Only in Japan, this variable was included in the top 8 variables, although its importance differed in time.

Third, the Posterior Inclusion Probability of PPP rate is the lowest among the group of analyzed countries. One can observe that in the beginning of the 1990's PIP of the PPP rate was close to zero, indicating that only in the more recent data the PPP rate played a more important role in shaping the GBP exchange rate.

Fourth, one can also observe substantial structural changes in the aftermath of the recent economic crisis - M2 monetary aggregate, general government debt and deficit saw a considerable increase in their Posterior Inclusion Probability after 2008. Such a result indicates that in the recent year monetary policy theories and Behavioral Equilibrium Exchange rates became more relevant in the case of the British pound.

Although changes in the δ forgetting factor were not substantial through most of the sample, there were two periods when the δ value dropped significantly. The first such period was the Great Recession in 2008-2009 and the second one was prior to the Brexit referendum in 2015, indicating that in those periods some structural changes took place in the British pound market.

Figure 5: Posterior weighted average estimate of δ (forgetting factor)



6 Application of model averaging in forecasting

In the assessment of the forecasting efficacy of the DMA combined models, I have used three methods. I began with direct forecasts of the exchange rates:

$$FX^f_{t+h} = Y_t \beta_t + \epsilon_t \tag{5}$$

where the FX^f_{t+h} is the forecasted value of the exchange rate at horizon h and the Y_t is the vector of predictors included in the model at time t. The major advantage of this method is that it does not need any forecasts of the explanatory variables to calculate forecasts. Evaluation of the forecasting capabilities on the basis of direct forecasts is very popular in articles using the DMA framework (see e.g. Koop and Korobilis, 2012; Buncic and Moretto, 2015; Catania and Nonejad, 2018, for studies focusing on the quality of direct forecasts). My major goal related to direct forecasts is to test whether macroeconomic fundamentals can be treated as leading indicators of exchange rate movements.

In the second method, I assumed that only naive forecast of the explanatory variables is available to calculate the exchange rate forecast:

$$FX^f_{t+h} = Y^f_{t+h} \beta_t + \epsilon_t \tag{6}$$

$$Y^f_{t+h} = Y_t \tag{7}$$

where the Y^f_{t+h} is the forecasted value of the predictors included in the model at horizon h. Intuitively, results obtained in such case should be very close to the random walk forecast of the exchange rate (otherwise it would mean that the in-sample model fit was of poor quality).

The third method is based on the perfect forecasts of the explanatory variables assumption, i.e. assuming that I knew the future values of the **explanatory** variables:

$$FX^f_{t+h} = Y_{t+h} \beta_t + \epsilon_t \tag{8}$$

where the Y_{t+h} is the vector of predictors included in the model at time $t + h$. In such a case, I provided the models with a distinct advantage over the random walk forecast. However, my goal was to evaluate what is the potentially highest forecasting accuracy gain possible, given that we have perfect foresight of the variables used in the models.

In order to collect the necessary amount of forecasting error data, I have used a rolling window contest to calculate forecasts over the 1, 2, 3, 4, 8 and 20 horizons. In the case of the Canadian dollar, Japanese Yen and British pound, the first windows were estimated based on the sample from 1st quarter 1980 to 4th quarter 2005 (i.e. 100 observations). Due to data availability, I have shortened the rolling window to 90 observations for the Swiss franc (data available from 1985 to 2018) and 60 observations for Euro (data available from 1996 to 2018). Next, I have moved the estimation window by one observation forward, re-estimated models and calculated forecasts. As a result, I have obtained up to 56 forecasts that were later evaluated on the basis of the Root Mean Square Forecast Error (RMSFE) statistic.

I compared the RMSFE statistic against the random walk (naive[3]) forecast, where I assumed that the exchange rate would not change in time. Apart from the Dynamic Model Averaging framework, I have also used three additional models as a benchmark. I began with the AR(4) model, where I only used the four lags of the exchange rate. Next, I have used the PPP calibrated model proposed by Ca' Zorzi et al. (2016), where I have used the following assumptions in the calibration process: the **real** exchange rate will gradually converge to the long-term mean with the half-life period equal to 12 quarters (i.e. after 12 quarters the distance from the long-term mean would decrease by half). The long-term mean was approximated by the 40 quarter average real exchange rate. Since this method focuses on the real exchange rate, I have assumed that the inflation rate among the two analysed economies would not change and therefore the same coefficient for real/nominal exchange rate ratio as in the last period used in the estimation can be applied. Apart from the DMA, I have also used the static (i.e. where the coefficients and PIPs cannot change in time) Bayesian Model Averaging framework to establish whether imposing the dynamic model structure offers gains concerning the forecasting capabilities. I tested the significance of the potential improvement in the forecast accuracy using the standard Diebold and Mariano (1995) test.

6.1 USD/CAD rate forecasts

In the case of the direct forecasts, the only case when Dynamic Model Averaging outperforms the random walk is the two-quarter horizon (see Table 2). However, this result is not statistically significant. Such an outcome indicates that macroeconomic variables used in this study were not leading indicators of the CAD/USD exchange rate movements.

As a result, I moved to the next method, where I did not use the lagged macroeconomic variables. The results are not significantly different from the naive CAD/USD forecast, which is not surprising given that such approach should yield similar results to the last observation in the sample.

In the last case, I assume that I have the perfect forecast of the explanatory variables. The results show a significant gain over the random walk indicating that it is possible to outperform the random walk (naive) forecast of the exchange rate using the macroeconomic fundamentals, however, it requires a sufficient quality of the forecast of those variables (i.e. better than the naive forecast). In this case, I do not analyze the PPP and the AR(4) models, as they would require knowledge about the future movements of the exchange rate itself[4].

Table 2: Quality forecasts of the CAD exchange rate against USD

RMSFE compared to naive forecast:

Direct forecasts						
Forecast horizon	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.0335	1.1232	1.1157	1.1288	1.2658	1.5300
PPP	1.0011	0.9914	1.0006	0.9960	1.0132	1.0289
Static BMA	1.0115	1.0311	1.0644	1.1272	1.7519	1.7375

[3]I will use the terms random walk forecast and naive forecast interchangeably

[4]In the case of the PPP model I would have to assume that I know the future real/nominal exchange rate ratio

Dynamic BMA	1.0652	0.9108	1.3000	1.4921	1.8328	1.3876
USD/CAD forecasts using naive forecasts of the explanatory variables						
	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.5302	1.1646	1.1300	1.0925	1.0565	1.0172
PPP	1.0011	0.9914	1.0006	0.9960	1.0132	1.0289
Static BMA	1.5387	1.1821	1.1219	1.0849	1.0560	1.0192
Dynamic BMA	1.2330	1.0230	1.0192	1.0179	1.0635	1.0187
USD/CAD forecasts using actual values of the explanatory variables for the forecast period						
	h=1	h=2	h=3	h=4	h=8	h=20
Static BMA	1.0103	**0.6699**	**0.5674**	**0.5022**	**0.3893**	**0.1949**
Dynamic BMA	1.0539	**0.8378**	**0.7674**	**0.7064**	**0.5642**	**0.5139**

Note: Bolded values indicate statistically significant improvement in forecasting capability according to Diebold and Mariano (1995) test at 0.05 probability.

6.2 USD/CHF rate forecasts

The results presented in table 3 display forecasting efficacy of the CHF/USD rate movements of the selected models. Obtained results show that none of the direct forecasts provided by analyzed models can outperform the naive forecast of the CHF/USD rate indicating that none of the potential exchange rate determinants identified in this study were leading indicators.

Next, I have used the naive forecasts of the macroeconomic variables to predict the USD/CHF exchange rate. In general, all the models included in the forecasting competition appear to have broadly similar accuracy, except the long-term horizon (over one year) forecasts of the PPP model that show much higher RMSFE values. The DMA forecast seems to have slightly lower RMSFE values than the naive forecast in most horizons. The Diebold and Mariano (1995) marked the difference in the statistical accuracy in the case of 4-quarter horizon forecast as significant, albeit the remaining test did not confirm this result.

Last but not least, I tested the assumption that a perfect forecast of the explanatory variables is available. In such a scenario, the results show a significant gain over the random walk (naive forecast). Such a result should be interpreted as showing that it is possible to outperform the random walk forecast of the USD/CHF exchange rate using the macroeconomic fundamentals. However, it requires sufficient (i.e. better than naive forecast) quality of macroeconomic variables forecast.

Table 3: Quality forecasts of the CHF exchange rate against USD

RMSFE compared to naive forecast:

Direct forecasts						
Forecast horizon	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.0324	1.1114	1.1950	1.2943	1.8500	4.4270
PPP	1.0323	1.0125	1.1215	1.2264	1.4576	1.8634
Static BMA	1.0420	1.0325	1.0614	1.3310	1.8617	2.0714
Dynamic BMA	1.0539	1.3345	1.6406	2.0455	1.9698	2.1071

USD/CHF forecasts using naive forecasts of the explanatory variables						
	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.3486	1.1126	1.1732	1.1041	1.1170	1.1123
PPP	1.0323	1.0125	1.1215	1.2264	1.4576	1.8634
Static BMA	1.3152	1.1061	1.1773	1.0764	1.1213	1.1183
Dynamic BMA	0.9935	0.9816	0.9979	**0.9817**	0.9905	1.0105
USD/CHF forecasts using actual values of the explanatory variables for the forecast period						
	h=1	h=2	h=3	h=4	h=8	h=20
Static BMA	1.0390	**0.7672**	**0.7080**	**0.6166**	**0.4864**	**0.2819**
Dynamic BMA	1.0175	**0.8815**	0.9507	**0.9214**	**0.8039**	**0.5153**

Note: Bolded values indicate statistically significant improvement in forecasting capability according to Diebold and Mariano (1995) test at 0.05 probability.

6.3 EUR/USD rate forecasts

The direct forecasts of the EUR/USD exchange rate, presented in Table 4, exhibit a somewhat different pattern than the CHF/USD rate. The PPP model produces forecasts with lower values of the RMSFE statistic and the difference is statistically significant in the long-term horizon. The DMA had better accuracy than the random walk model in the case of 8-quarter forecasts, albeit it also had much worse result in some other cases. Consequently, it appears that the macroeconomic variables were not leading indicators of the EUR/USD exchange rate movements.

Furthermore, the DMA forecasts generally improved their RMSFE statistic in the case of second method (based on naive forecasts of the explanatory variables). Such an outcome adds another argument in favour of the hypothesis that exchange rate does not react with delay to the changes in macroeconomic variables. The PPP models, also in this case, managed to outperform the random walk in the long-term horizons.

Perfect knowledge of the future values of the macroeconomic variables gives a vast advantage over the random walk model. As a result, in the case of third method, both BMA and DMA algorithms managed to substantially outperform the random walk in forecasting the EUR/USD rate (except the one period ahead forecast, where the results are roughly similar).

Table 4: Quality forecasts of the EUR exchange rate against USD

RMSFE compared to naive forecast:

Direct forecasts						
Forecast horizon	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.0635	1.1017	1.3023	1.2226	1.2168	1.0735
PPP	0.9832	0.9557	0.9628	0.9485	**0.9209**	**0.8169**
Static BMA	1.0564	1.1433	1.2739	1.1222	1.1331	1.0182
Dynamic BMA	1.0432	1.0728	1.2563	1.0987	**0.9019**	1.3111
EUR/USD forecasts using naive forecasts of the explanatory variables						
	h=1	h=2	h=3	h=4	h=8	h=20

AR(4)	1.3592	1.0955	1.1806	1.0191	1.0042	1.0036
PPP	0.9832	0.9557	0.9628	0.9485	**0.9209**	**0.8169**
Static BMA	1.4276	1.1056	1.1870	0.9923	0.9771	0.9930
Dynamic BMA	1.1762	1.0023	1.0878	0.9716	1.0209	0.9770
EUR/USD forecasts using actual values of the explanatory variables for the forecast period						
	h=1	h=2	h=3	h=4	h=8	h=20
Static BMA	1.0544	**0.7294**	**0.6293**	**0.4870**	**0.3677**	**0.2075**
Dynamic BMA	1.0485	**0.7687**	**0.7535**	**0.6839**	**0.5853**	**0.1936**

Note: Bolded values indicate statistically significant improvement in forecasting capability according to Diebold and Mariano (1995) test at 0.05 probability.

6.4 USD/JPY rate forecasts

Forecasting of the USD/JPY rate performance results presented in Table 5 indicate that the PPP calibrated model offered the least accurate forecasts. The remaining models produced direct forecasts with broadly similar accuracy to the random walk, albeit in the longest horizon, equal to five years, some gains over the naive forecasts can be observed. The DMA forecasts offered the best forecast in the 20 quarter horizon that and significantly better than the random walk forecast.

Similar to the other currencies, the naive forecasts of the macroeconomic variables do not provide enough information to predict the USD/JPY rate movements accurately. The obtained RMSFE statistics are generally very close to the naive forecasts in the case of PPP and DMA models. The static BMA and AR(4) tend to perform worse in the short-term horizon (up to four quarters).

In the last case, I assume that I have the perfect forecast of the explanatory variables. Interestingly, the DMA model offers substantial gains in accuracy even in the case of the one quarter ahead forecasts, which was not the case for the previously analysed currencies.

Table 5: Quality forecasts of the JPY exchange rate against USD

RMSFE compared to naive forecast:

Direct forecasts						
Forecast horizon	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.0175	0.9616	0.9687	1.0219	0.9882	0.9019
PPP	1.0062	1.0180	1.0935	1.1064	1.1330	1.1116
Static BMA	0.9997	1.0308	1.2122	1.2914	1.4091	0.8312
Dynamic BMA	0.9390	0.9854	1.1497	1.1671	1.6146	**0.7365**
USD/JPY forecasts using naive forecasts of the explanatory variables						
	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.4230	1.1195	1.1961	1.1922	1.0612	1.0049
PPP	1.0062	1.0180	1.0935	1.1064	1.1330	1.1116
Static BMA	1.3981	1.0879	1.1992	1.1948	1.0535	0.9957
Dynamic BMA	1.0016	0.9524	1.0769	1.0767	1.0423	1.0096
USD/JPY forecasts using actual values of the explanatory variables for the forecast period						

	h=1	h=2	h=3	h=4	h=8	h=20
Static BMA	0.9792	**0.6561**	**0.5835**	**0.4831**	**0.2980**	**0.1599**
Dynamic BMA	**0.8788**	**0.6572**	**0.6108**	**0.5548**	**0.3829**	**0.3422**

Note: Bolded values indicate statistically significant improvement in forecasting capability according to Diebold and Mariano (1995) test at 0.05 probability.

6.5 USD/GBP rate forecasts

The last currency analysed in this study is the USD/GBP exchange rate and Table 6 displays the results regarding the obtained forecasts. Simple models, such as the AR(4) and the calibrated PPP model, performed better than model averaging algorithms in the case of the direct forecasts of USD/GBP rate. Moreover, the PPP model in the longest direct forecast horizon showed significant improvement in the forecasting accuracy compared to the naive forecast according to two out of three used tests.

To better understand the practicality of model averaging algorithms in the forecasting of the British pound movements I have also studied the exchange rate forecasts based on the naive forecasts of the macroeconomic variables. Obtained results for the BMA and DMA algorithms are very similar to the naive forecasts confirming that good forecasts of macroeconomic variables are the necessary condition for macroeconomic models to outperform the random walk forecast.

In the last case, I assume that I have the perfect forecast of the macroeconomic variables. The results show a significant gain over the random walk (except the one quarter horizon forecast). Such result should be interpreted as showing that it is possible to outperform the naive forecast of the USD/GBP exchange rate using the macroeconomic fundamentals, albeit it requires information about the future values of the macroeconomic variables.

Table 6: Quality forecasts of the GBP exchange rate against USD

RMSFE compared to naive forecast:						
Direct forecasts						
Forecast horizon	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.0679	1.0415	1.1114	1.0978	1.1853	0.7817
PPP	0.9962	0.9965	1.0278	1.0099	1.0764	**0.7560**
Static BMA	1.0210	0.9916	1.1160	1.3076	1.1825	1.0004
Dynamic BMA	1.0267	0.9416	1.2809	1.5301	1.5013	1.4061
USD/GBP forecasts using naive forecasts of the explanatory variables						
	h=1	h=2	h=3	h=4	h=8	h=20
AR(4)	1.4945	1.1031	1.1025	1.0443	1.0788	0.9857
PPP	0.9962	0.9965	1.0278	1.0099	1.0764	**0.7560**
Static BMA	1.5240	1.1243	1.1017	1.0289	1.0819	0.9905
Dynamic BMA	1.2232	1.0280	0.9874	0.9682	1.0436	0.9839
USD/GBP forecasts using actual values of the explanatory variables for the forecast period						
	h=1	h=2	h=3	h=4	h=8	h=20
Static BMA	1.0145	**0.6480**	**0.5703**	**0.5143**	**0.3906**	**0.2501**

Dynamic BMA	0.9976	0.8434	**0.8017**	**0.7326**	**0.6846**	**0.5917**

Note: Bolded values indicate statistically significant improvement in forecasting capability according to Diebold and Mariano (1995) test at 0.05 probability.

7 Conclusions

The importance of the variables in the exchange rate forecasting can substantially differ both in time and across the countries. The recent Great Recession and the European sovereign debt crisis saw a substantial increase in the volatility in the exchange rates that also lead to some structural changes in the crucial determinants of the currency movements, that can be indirectly observed by the decrease of the δ forgetting factor in the DMA framework. Presented results showed that in the case of euro, the general government deficit, current account balance and the CPI inflation rate, as well as the GDP per capita, have substantially increased their Posterior Inclusion Probabilities. One can also observe substantial structural changes in the aftermath of the recent economic crisis in the British pound market - M2 monetary aggregate, general government debt and deficit saw a considerable increase in their Posterior Inclusion Probability after 2008. In contrast to this, neither government deficit nor the GDP growth proved to be important in the case of the Swiss franc. Interestingly, lagged value of economic sentiments, measured with the Composite Leading Indicator (CLI), increased their importance for the Japanese yen in recent years.

It is worth noting that there were also some variables with high Posterior Inclusion Probabilities among all the analyzed currencies. To begin with, the lagged value of the exchange rate always remains a vital variable indicating significant persistence in the exchange rate time series. Moreover, variables such as the PPP rate, Terms of Trade (TOT) and output per worker have high Posterior Inclusion Probabilities among all the analyzed countries.

In the second part of the analysis, I have focused on the predictive capabilities of the macroeconomic fundamentals. Macroeconomic variables do not offer any predictive gains over the random walk (naive) forecast in the case of direct forecasts, which indicates that they should not be viewed as leading indicators of exchange rate movements. The foreign exchange market seems to react to changes in the macroeconomic environment instantaneously. As a result, I have also presented two approaches based on the forecasted values of macroeconomic variables. In such a case, macroeconomic variables can offer substantial predictive power, conditional on the quality of the macroeconomic variables forecast. Unfortunately, more accurate than the random walk forecast of the exchange rate requires more accurate than a random walk forecast of the explanatory macroeconomic variables. In some cases, it might be an easier task, especially in the case of simplified framework based on PPP that also seemed to perform quite well and it requires only a reasonable forecast of the inflation rates (as it provides forecasts of the real exchange rate that needs to be recalculated to get the nominal exchange rate).

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Appendix

Figure 6: Posterior Inclusion Probabilities of the key variables for USD/CAD exchange rate forecasts

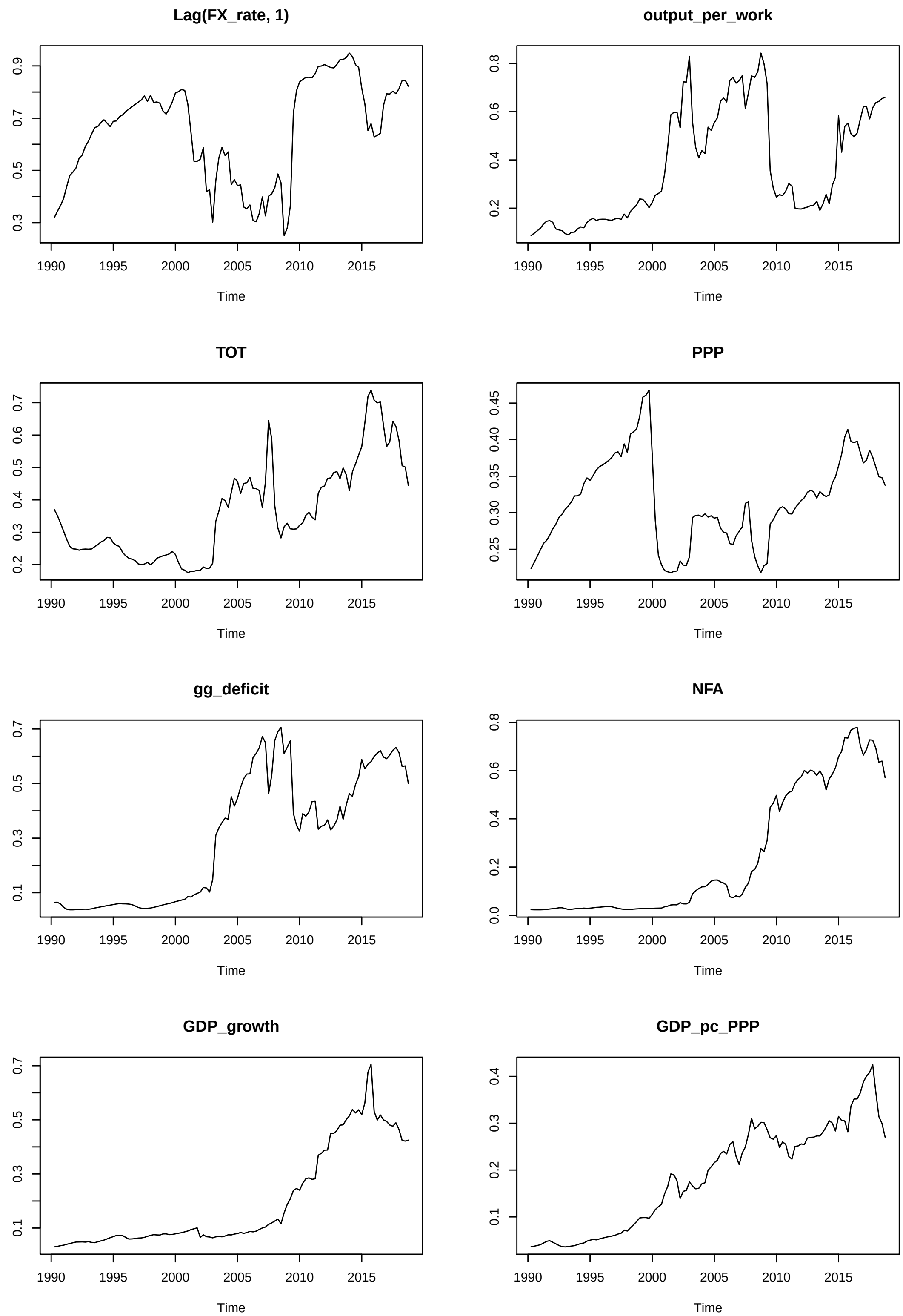

Figure 7: Posterior Inclusion Probabilities of the key variables for USD/CHF exchange rate forecasts

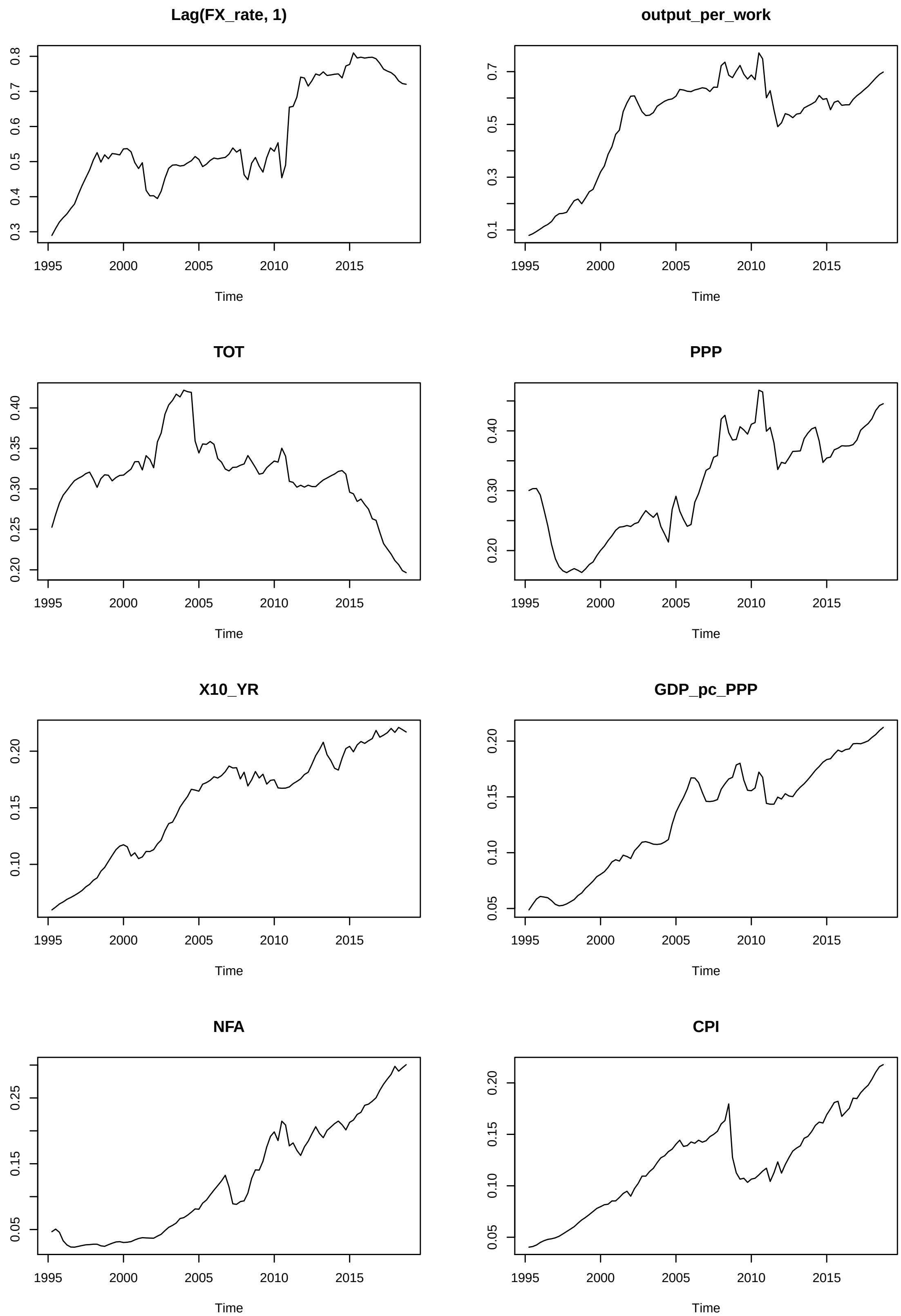

Figure 8: Posterior Inclusion Probabilities of the key variables for EUR/USD exchange rate forecasts

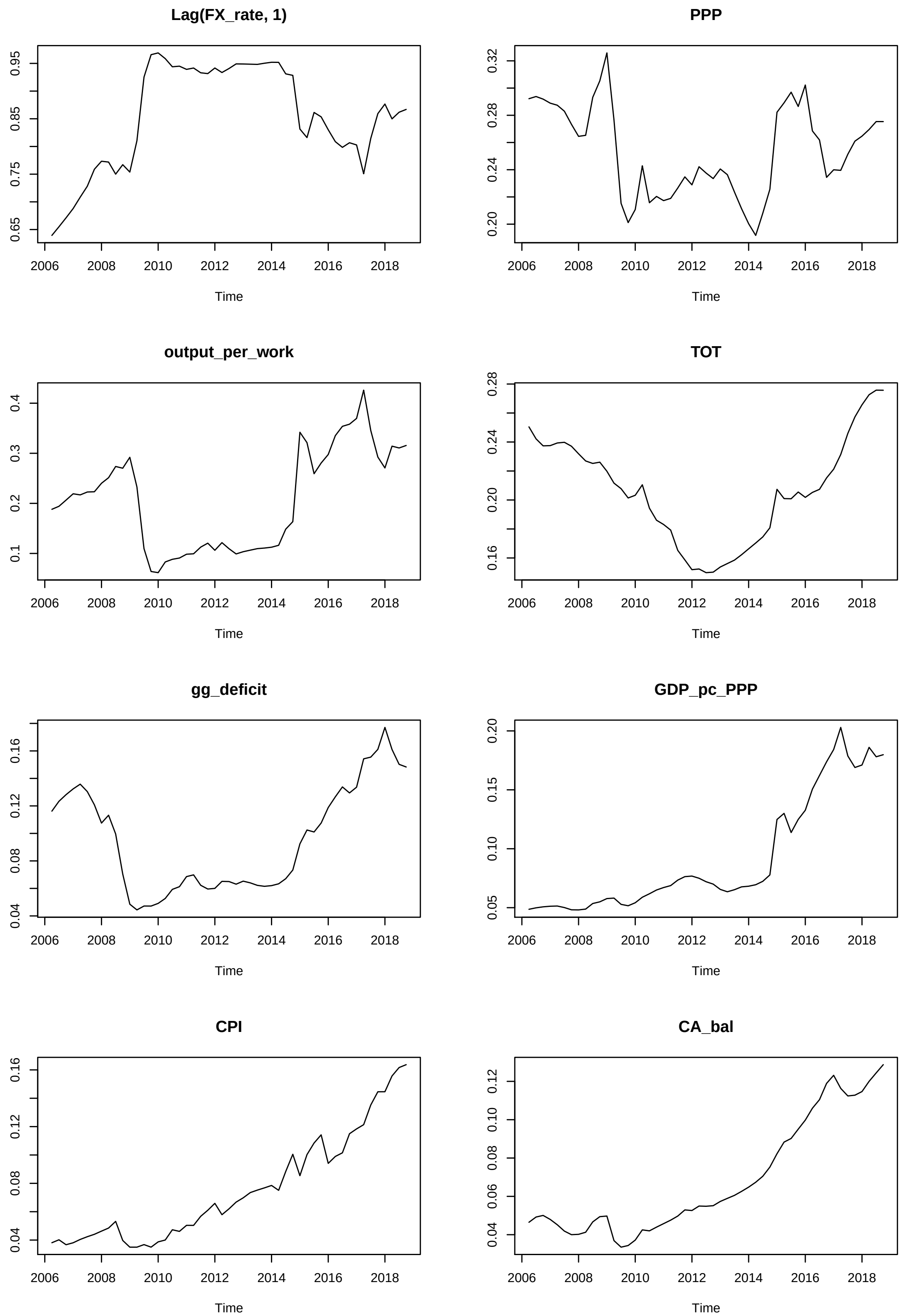

Figure 9: Posterior Inclusion Probabilities of the key variables for USD/JPY exchange rate forecasts

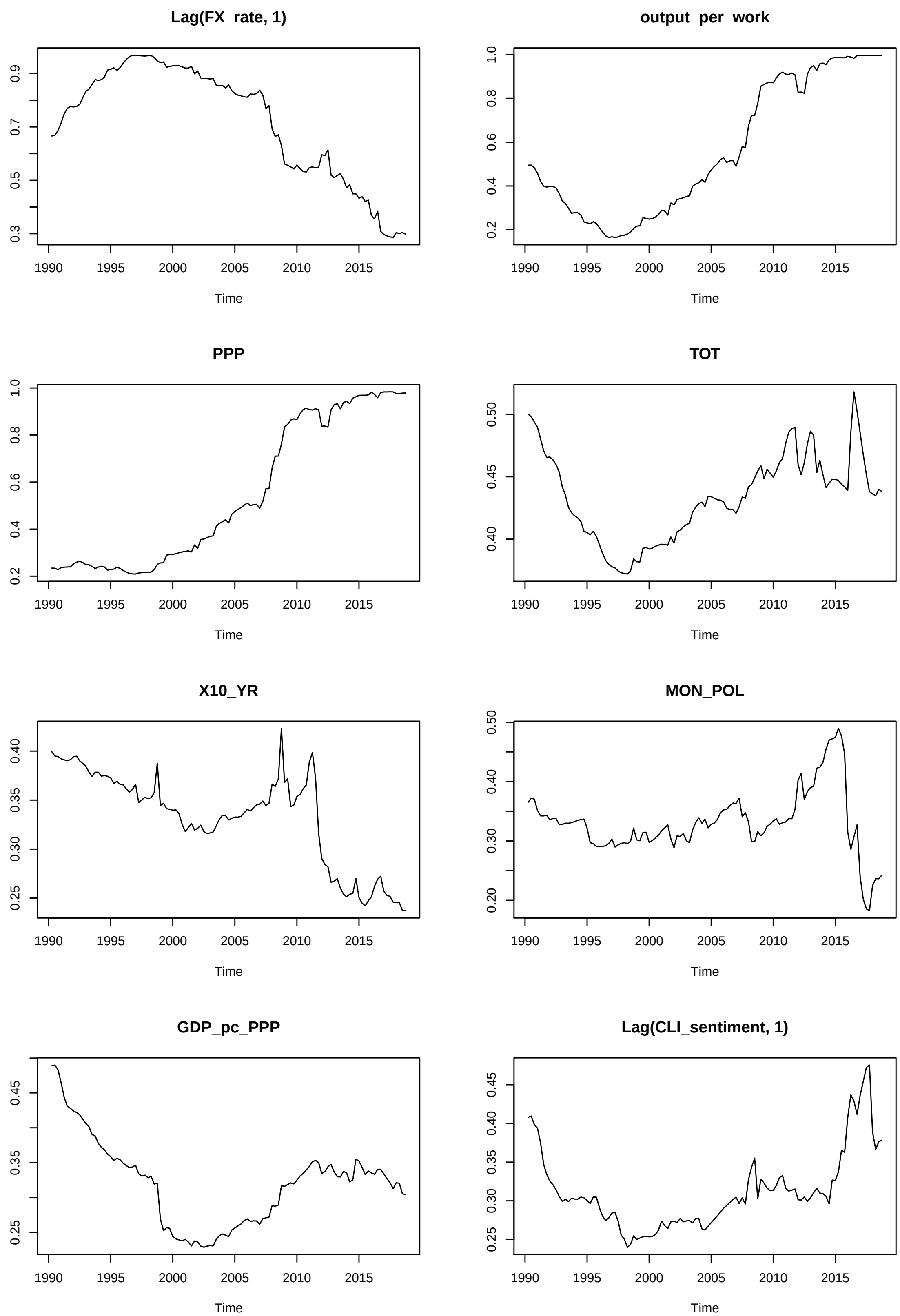

Figure 10: Posterior Inclusion Probabilities of the key variables for USD/GBP exchange rate forecasts