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Jaroslava Hlouskova



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Author(s):

Mauro Costantini, Jesús Crespo-Cuaresma, Jaroslava Hlouskova

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Can Macroeconomists Get Rich Forecasting Exchange Rates?

Mauro Costantini¹, Jesus Crespo Cuaresma² and Jaroslava Hlouskova³

¹Brunel University

²Vienna University of Economics and Business

³Institute for Advanced Studies, Vienna

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Can Macroeconomists Get Rich Forecasting Exchange Rates?*

Mauro Costantini[†]

Jesus Crespo Cuaresma[‡]

Jaroslava Hlouskova[§]

Abstract

We provide a systematic comparison of the out-of-sample forecasts based on multivariate macroeconomic models and forecast combinations for the euro against the US dollar, the British pound, the Swiss franc and the Japanese yen. We use profit maximization measures based on directional accuracy and trading strategies in addition to standard loss minimization measures. When comparing predictive accuracy and profit measures, data snooping bias free tests are used. The results indicate that forecast combinations help to improve over benchmark trading strategies for the exchange rate against the US dollar and the British pound, although the excess return per unit of deviation is limited. For the euro against the Swiss franc or the Japanese yen, no evidence of generalized improvement in profit measures over the benchmark is found.

JEL codes: C53, F31, F37

Keywords: Exchange rate forecasting, forecast combination, multivariate time series models, profitability

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[†]Department of Economics and Finance, Brunel University, London, UK

[‡]Department of Economics, Vienna University of Economics and Business; Wittgenstein Centre for Demography and Global Human Capital (WIC); World Population Program, International Institute of Applied Systems Analysis (IIASA) and Austrian Institute for Economic Research (WIFO), Vienna, Austria

[§]Department of Economics and Finance, Institute for Advanced Studies, Vienna, Austria, and Department of Economics, Thompson Rivers University, Kamloops, BC, Canada

1 Introduction

Forecasting exchange rates is a notoriously difficult task. Myriads of empirical studies (see for example the recent survey by James et al., 2012) document the challenges associated with specifying macro-econometric models with good predictive performance for exchange rate data, in particular for short-run forecasting horizons.

Since the seminal work by Meese and Rogoff (1983), which shows that specifications based on macroeconomic fundamentals are unable to outperform simple random walk forecasts, a large number of studies have proposed models aimed at providing accurate out-of-sample predictions of spot exchange rates (see MacDonald and Taylor, 1994; Mark, 1995; Chinn and Meese, 1995; Kilian, 1999; Mark and Sul, 2001; Berkowitz and Giorgianni, 2001; Cheung et al.; 2005, or Boudoukh et al., 2008, among others). In parallel, a literature has emerged which examines empirically the potential profitability of technical trading rules (see Menkhoff and Taylor, 2007, for a review). The analysis of profitability of technical trading rules can be thought of as a simple and robust test for the weak form of the efficient market hypothesis, which concludes that if the foreign exchange market is efficient, one should not be able to use publicly available information to correctly forecast changes in exchange rates and thus make an abnormal profit.

The aim of this paper is to provide a systematic comparison of out-of-sample forecast accuracy in terms of predictive error, directional accuracy and profitability of trading strategies for the euro against the US dollar, the British pound, the Swiss franc and the Japanese yen. To the best of our knowledge, the closest paper to ours is Yang et al. (2008), who applied the nonlinear approach of Hong and Lee (2003) to test the martingale hypothesis of the daily euro exchange rate against seven currencies. However, our analysis differs from theirs in many respects. First, we use monthly data and apply several multivariate macro-econometric models.¹ Second, in addition to standard loss measures based on prediction errors, recently developed directional forecast accuracy measures are also considered. The latter measures account for both the realized directional changes in exchange rates as well as for their magnitudes (see Blaskowitz and Herwartz, 2009, 2011; Bergmeir et al., 2014). This is the first innovation of the paper relative to the existing literature. Such measures are robust to outliers and provide an economically interpretable loss/success functional framework in a decision-theoretical context, which is extremely relevant for traders and investors. Third, this paper not only tests for the predictability of the euro exchange rate based on both loss and directional accuracy measures using a benchmark random walk model, but it also compares the (risk adjusted) profits generated by forecast-based

¹Yang et al. (2008), on the other hand, use daily data and thus suggest exploring the predictability of the euro exchange rate for a different frequency.

trading strategies to those using benchmark trading rules. The comparison of predictive accuracy and profit measures is assessed using the following data snooping bias free tests that are based on extensive bootstrap-based procedure: the ‘reality check’ (RC) test of White (2000), the test for superior predictive ability (SPA) by Hansen (2005), the stepwise test of multiple reality check (StepM-RC) by Romano and Wolf (2005) and the stepwise multiple superior predictive ability (StepM-SPA) test by Hsu et al. (2010). Fourth, and this is the second novelty of the paper, we exploit the potential of a large number of forecast combination methods for both forecast accuracy evaluation and profitability. In doing so, we propose a new method of combination based on the economic evaluation of directional forecasts. The other methods of combination used are the mean, median or trimmed mean, the ordinary least squares combining methods, combinations based, on principal components, on discounted mean square forecast errors, on hit rates and on Bayesian and frequentist model averaging techniques are considered.

The results of our analysis indicate that forecast combinations, and in particular forecast pooling based on principal components, tend to improve profitability of trading rules as compared to benchmark strategies and strategies based on single multivariate time series specifications for the EUR/USD and EUR/GBP rates. Such an improvement, however, is by no means systematic across profitability measures and forecasting horizons. In addition, the comparison of the realized Sharpe ratios reveals that the margin for achieving systematic profits in the foreign exchange market using the information contained by macroeconomic variables is very small. On the other hand, the forecasts of the EUR/CHF exchange rate based on both individual models and forecast combinations do outperform the random walk model for a long-term prediction horizon. For the case of the EUR/JPY exchange rates, on the other hand, we find no robust improvement over standard benchmarks.

The rest of the paper is organized as follows. Section 2 describes the analytical framework used, including the forecast combination approaches and the forecast accuracy measures, as well as the trading strategies they are based on. In section 3, the design of the empirical exercise and the testing procedures for data snooping biases are presented. The results are discussed in section 4 and section 5 concludes.

2 Analytical framework

2.1 The monetary model of exchange rates

The theoretical framework of the monetary model of exchange rate formation (for the original formulations, see Frenkel, 1976; Dornbusch, 1976; Hooper and Morton, 1982) has become the

workhorse for constructing macroeconomic models aimed at exchange rate prediction. Let real money demand in the domestic and foreign economies be given by log-linear functions,

$$M_t^d - P_t^d = \beta^d Y_t^d - \gamma^d i_t^d, \quad (1)$$

$$M_t^f - P_t^f = \beta^f Y_t^f - \gamma^f i_t^f, \quad (2)$$

where M_t refers to (log) nominal money demand, P_t is (the log of) the price level, Y_t is (log) income and i_t is the interest rate. The superindices d and f identify the parameters and variables of the domestic and foreign economy, respectively. If the (long-run) equilibrium exchange rate is assumed to be given by purchasing power parity, then

$$s_t = P_t^d - P_t^f, \quad (3)$$

where s_t denotes the (log) nominal exchange rate; i.e., $s_t = \log(S_t)$ and thus S_t is the exchange rate of the domestic currency against the foreign currency. Combining equation (1) and (2) with the equilibrium condition given by equation (3) results in

$$s_t = M_t^d - M_t^f + \beta^f Y_t^f - \beta^d Y_t^d + \gamma^d i_t^d - \gamma^f i_t^f, \quad (4)$$

a specification that suggests a relationship between the exchange rate, the money stock, output and interest rates. The empirical literature on exchange rate modelling and forecasting based on the monetary model of exchange rate determination often combines these variables in the form of vector autoregressive (VAR) models, so that

$$x_t = \psi(0) + \sum_{l=1}^p \psi(l)x_{t-l} + \varepsilon_t, \quad \varepsilon_t \sim \mathbf{NID}(\mathbf{0}, \Sigma_\varepsilon), \quad (5)$$

where $\psi(l)$ ($l = 1, \dots, p$) are matrices of coefficients. The x_t vector in our model is composed by the corresponding exchange rate (s_t), an output measure for the domestic and foreign economy (Y_t^d and Y_t^f), money supply² in the domestic and foreign economy (M_t^d and M_t^f), as well as short and long-term interest rates in both countries ($i_t^{s,d}$, $i_t^{l,d}$, $i_t^{s,f}$ and $i_t^{l,f}$). If the variables of the model are linked by some cointegration relationship, the model in (5) can be written as a vector error correction (VEC) model

$$\Delta x_t = \delta(0) + \alpha \beta' x_{t-1} + \sum_{l=1}^p \delta(l) \Delta x_{t-l} + \varepsilon_t, \quad \varepsilon_t \sim \mathbf{NID}(\mathbf{0}, \Sigma_\varepsilon), \quad (6)$$

²We consider the model in equilibrium, thus money demand equals to money supply.

where the cointegration relationships are given by $\beta'x_t$ and α measures the speed of adjustment to the long run equilibrium. Alternatively, if the variables in x_t are unit-root nonstationary but no cointegration relationship exists among them, a VAR model in first differences (DVAR) would be the appropriate representation,

$$\Delta x_t = \psi(0) + \sum_{l=1}^{p-1} \psi(l)\Delta x_{t-l} + \varepsilon_t, \quad \varepsilon_t \sim \mathbf{NID}(\mathbf{0}, \Sigma_\varepsilon). \quad (7)$$

If the income and interest rate elasticities of money demand are assumed equal for the domestic and foreign economy, the multivariate models above can be rewritten using vectors of differences in the variables, so that $x_t = (s_t, m_t, y_t, i_t^s, i_t^l) = (s_t, M_t^d - M_t^f, Y_t^d - Y_t^f, i_t^{s,d} - i_t^{s,f}, i_t^{l,d} - i_t^{l,f})$. We refer to models containing these variables as *restricted* models, while the models based on separated domestic and foreign variables are labeled *unrestricted* models.

The monetary model rests on two important simplifying assumptions: (i) domestic and foreign assets are perfect substitutes (implying perfect capital mobility) and (ii) current account effects (surplus or deficit) are negligible. These assumptions can be relaxed if the role of capital flows in explaining exchange rate movements is taken into account (see Bailey et al., 2001; Aliber, 2000). Thus, it might be possible to tie together movements in the exchange rates, the real interest rate, equity prices and current account balance. Current account dynamics can be thought of as the result of changes in productivity. For instance, if a positive productivity shock raises expected future output in the domestic economy, capital inflows are induced for at least two reasons. On the one hand, if consumers in the home economy expect to be richer in the future, they will want to borrow from abroad to increase their consumption today (assuming they are sufficiently forward-looking to smooth their consumption over time). On the other hand, the expected increase in future productivity raises expected future profits, increasing equity prices, thereby stimulating investment demand; insofar the additional demand for funds to finance such investment is not available domestically, which causes inflows of capital (foreign direct investment and portfolio investment). Such arguments call for the inclusion of capital flow variables or proxies thereof into the exchange rate models. In addition to the unrestricted and restricted monetary model specifications, we consider a class of models which substitutes the output and money supply variables in the monetary model by a leading indicator variable and a stock market index. These specifications are labelled *capital flows* models.

Finally, for the empirical implementation of the models in the form of VAR specifications, we consider both parametrizations which include all variables and their respective lags as well as specifications where insignificant lags are omitted (subset-VAR models).

2.2 Forecasts and combinations

The aim of our analysis is to assess the profitability of trading strategies based on out-of-sample predictions of individual VAR, VEC and DVAR models, as well as combinations of these. Let us denote $\hat{S}_{i,t+h|t}$ the exchange rate forecast obtained using model i , $i = 1, \dots, k$, for time $t + h$ conditional on the information available at time t (i.e., h is the forecast horizon). Pooled forecasts, $\hat{S}_{c,t+h|t}$, take the form of a linear combination of the predictions of individual specifications,

$$\hat{S}_{c,t+h|t} = w_{c,0t}^h + \sum_{i=1}^k w_{c,it}^h \hat{S}_{i,t+h|t}, \quad (8)$$

where c is the combination method, k is the number of individual forecasts and the weights are given by $\{w_{c,it}^h\}_{i=0}^k$.

Since several combination methods require statistics based on a hold-out sample, let us introduce here some notation on the subsample limits: T_0 is used to denote the first observation of the available sample, the interval (T_1, T_2) is used as a hold-out sample used to obtain weights for those methods where such a subsample is required and T_3 is the last available observation. The sample given by (T_2, T_3) is the proper out-of-sample period used to compare the different methods.

We consider a large number of combination methods proposed in the literature:

- (i) *Mean, trimmed mean, median.* With regard to the mean, $w_{\text{mean},0t}^h = 0$ and $w_{\text{mean},it}^h = \frac{1}{k}$ in equation (8). The trimmed mean uses $w_{\text{trim},0t}^h = 0$ and $w_{\text{trim},it}^h = 0$ for the individual models that generate the smallest and largest forecasts, while $w_{\text{trim},it}^h = \frac{1}{k-2}$ for the remaining individual models. For the median combination method, $\hat{S}_{c,t+h|t} = \text{median}\{\hat{S}_{i,t+h|t}\}_{i=1}^k$ is used (see Costantini and Pappalardo, 2010).
- (ii) *Ordinary least squares (OLS) combination* (see Granger and Ramanathan, 1984). The method estimates the parameters in equation (8) using recursive and rolling windows. In the recursive case, to compute the initial OLS combination forecast, for S_{T_2} , we regress $\{S_{t+h}\}_{t=T_1-1}^{T_2-2h}$ on a constant and $\{\hat{S}_{i,t+h|t}\}_{t=T_1-1}^{T_2-2h}$, $i = 1, \dots, k$, and set the weights in equation (8), w_{OLS,i,T_2-h}^h , equal to the estimated OLS coefficients. To construct the second combination forecast, for S_{T_2+1} , the OLS coefficients are estimated by regressing $\{S_{t+h}\}_{t=T_1-1}^{T_2-2h+1}$ on a constant and $\{\hat{S}_{i,t+h|t}\}_{t=T_1-1}^{T_2-2h+1}$, $i = 1, \dots, k$, and the fitted OLS coefficients, $w_{\text{OLS},i,T_2-h+1}^h$, are used as weights for equation (8). This procedure is applied until the available out-of-sample period; i.e., the weights of the h -step ahead forecast for S_{T_3} are obtained by regressing $\{S_{t+h}\}_{t=T_1-1}^{T_3-2h}$ on a constant and $\{\hat{S}_{i,t+h|t}\}_{t=T_1-1}^{T_3-2h}$, $i = 1, \dots, k$.

In the case of the rolling window, we proceed in a similar fashion but discard the first observations in each replication of the procedure, so that the time series are consistently of length $T_2 - T_1 - 2h + 2$. Thus, for the second combination forecast S_{T_2+1} , for instance, we regress $\{S_{t+h}\}_{t=T_1}^{T_2-2h+1}$ on a constant and $\{\hat{S}_{i,t+h|t}\}_{t=T_1}^{T_2-2h+1}$, $i = 1, \dots, k$ and for the last combination forecast S_{T_3} , we regress $\{S_{t+h}\}_{t=T_3-2h}^{T_3-2h}$ on a constant and $\{\hat{S}_{i,t+h|t}\}_{t=T_3-2h}^{T_3-2h}$, $i = 1, \dots, k$.

- (iii) *Combination based on principal components (PC)*. This method allows to overcome multicollinearity when having many forecasts by reducing them to a few principal components (factors). The method is identical to the OLS combining method by replacing forecasts by their principal components and thus equation (8) changes to

$$\hat{S}_{\text{PC},t+h|t} = w_{\text{PC},0t}^h + \sum_{i=1}^{k_{h,t-h}} w_{\text{PC},it}^h f_{it}^h, \quad (9)$$

where $1 \leq k_{h,t-h} \leq k$ is the number of principal components extracted based on the information available at $t-h$ and $f_{1t}^h, \dots, f_{k_{h,t-h}t}^h$ are the first $k_{h,t-h}$ principal components for $\hat{S}_{1t}^h, \dots, \hat{S}_{k_{h,t-h}t}^h$. In our application, we choose the number of principal components using the so-called variance proportion criterion, which selects the smallest number of principal components such that a certain fraction (α) of variance is explained. In our application we set $\alpha = 0.8$. Hlouskova and Wagner (2013), where the principal components augmented regressions were used in the context of the empirical analysis of economic growth differentials across countries, provide more details on the method.³

- (iv) *Combination based on the discount mean square forecast errors (DMSFE)*. Following Stock and Watson (2004), the weights in equation (8) depend inversely on the historical forecasting performance of the individual models

$$w_{\text{DMSFE},i,t}^h = \frac{m_{ith}^{-1}}{\sum_{l=1}^k m_{lth}^{-1}}, \quad (10)$$

where

$$m_{ith} = \sum_{s=T_1-1+h}^t \theta^{T-h-s} \left(S_{s+h} - \hat{S}_{i,s+h|s}^h \right)^2, \quad (11)$$

³We are not aware of the existence of any study using this approach in the context of the exchange rate forecasts.

for $t = T_2 - h, \dots, T_3 - h$, $i = 1, \dots, k$, $w_{\text{DMSFE},0,t} = 0$ and θ is a discount factor. When $\theta = 1$ there is no discounting, while if $\theta < 1$, greater importance is attributed to the recent forecast performance of the individual models. In the empirical application, we use alternatively $\theta = 0.95$.

- (v) *Combination based on hit/success rates (HR)*. The method uses the proportion of correctly predicted directions of exchange rate changes of model i to the number of all correctly predicted directions of exchange rate changes by the models entertained,

$$w_{\text{HR},it}^h = \frac{\sum_{j=T_1+h-1}^t DA_{jh}^i}{\sum_{l=1}^k \left(\sum_{j=T_1+h-1}^t DA_{jh}^l \right)} \quad (12)$$

where $t = T_2 - h, \dots, T_3 - h$ and the index of directional accuracy is given by $DA_{jh} = I\left(\text{sgn}(S_j - S_{j-h}) = \text{sgn}(\hat{S}_{j|j-h} - S_{j-h})\right)$, where $I(\cdot)$ is the indicator function.

- (vi) *Combination based on the exponential of hit/success rates (EHR)* (Bacchini et al., 2010). The weights in this method are obtained as

$$w_{\text{EHR},it}^h = \frac{\exp\left(\sum_{j=T_1+h-1}^t (DA_{jh}^i - 1)\right)}{\sum_{l=1}^k \exp\left(\sum_{j=T_1+h-1}^t (DA_{jh}^l - 1)\right)} \quad (13)$$

where $t = T_2 - h, \dots, T_3 - h$.

- (vii) *Combination based on the economic evaluation of directional forecasts (EEDF)*. It uses weights that capture the ability of models to predict the direction of change of the exchange rate taking into account the magnitude of the realized change,

$$w_{\text{EEDF},it}^h = \frac{\sum_{j=T_1+h-1}^t DV_{jh}^i}{\sum_{l=1}^k \left(\sum_{j=T_1+h-1}^t DV_{jh}^l \right)} \quad (14)$$

where $t = T_2 - h, \dots, T_3 - h$ and $DV_{th} = |S_t - S_{t-h}| DA_{th}$.

- (viii) *Combination based on predictive Bayesian model averaging (BMA)*. The weights used are based on the corresponding posterior model probabilities based on out-of-sample (rather than in-sample) fit. See for example Raftery et al. (1997), Carriero et al. (2009), Crespo

Cuaresma (2007), Feldkircher (2012).

$$w_{\text{BMA},it}^h = P(M_i | \mathbf{S}_{T_1+h-1:t}) = \frac{P(\mathbf{S}_{T_1+h-1:t} | M_i) P(M_i)}{\sum_{l=1}^k P(\mathbf{S}_{T_1+h-1:t} | M_l) P(M_l)}, \quad (15)$$

where $P(M_i | \mathbf{S}_{T_1+h-1:t})$ is the posterior model probability of model i , $P(\mathbf{S}_{T_1+h-1:t} | M_i)$ is the marginal likelihood of the model and $t = T_2 - h, \dots, T_3 - h$. Using the predictive likelihood in order to address the out-of-sample fit of each model and assuming equal prior probability across models, $P(M_l)$, the weights can be approximated as

$$w_{\text{BMA},it}^h = \frac{(t - T_1 - h + 2)^{\frac{p_1 - p_i}{2}} \left(\frac{\sum_{j=T_1+h-1}^t MSE_{jh}^1}{\sum_{j=T_1+h-1}^t MSE_{jh}^i} \right)^{\frac{t - T_1 - h + 2}{2}}}{\sum_{l=1}^k (t - T_1 - h + 2)^{\frac{p_1 - p_l}{2}} \left(\frac{\sum_{j=T_1+h-1}^t MSE_{jh}^1}{\sum_{j=T_1+h-1}^t MSE_{jh}^l} \right)^{\frac{t - T_1 - h + 2}{2}}}, \quad (16)$$

where MSE_{jh}^i is the mean squared error of model i , namely $MSE_{jh}^i = \left(\hat{S}_{i,j|j-h} - S_j \right)^2$.

(ix) *Combinations based on frequentist model averaging (FMA)* (see Claeskens and Hjort, 2008, and Hjort and Claeskens, 2003). The weights are calculated as follows

$$w_{\text{FMA},it}^h = \frac{\exp\left(-\frac{1}{2}IC_t^i\right)}{\sum_{l=1}^k \exp\left(-\frac{1}{2}IC_t^l\right)} \quad (17)$$

where IC_t^i stands for an information criterion of model i and t is the last time point of the data over which are models estimated.

We use combinations of forecasts based on the Akaike criterion (AIC), Schwarz criterion (BIC) and Hannan-Quinn criterion (HQ). The weights corresponding to the BIC can be interpreted as an approximation to the posterior model probabilities in BMA (see Raftery et al., 1997; Sala-i-Martin et al., 2004).

2.3 Predictive accuracy: Loss and profit measures

We evaluate the exchange rate forecasts using performance measures based on both profit maximization and the loss minimization. The loss measures include the standard mean squared error, $MSE_{th} = (\hat{S}_{t|t-h} - S_t)^2$ and the mean absolute error, $MAE_{th} = |\hat{S}_{t|t-h} - S_t|$, which have been routinely used in most empirical assessments of exchange rate forecasting models. The former include the directional accuracy measure (DA), the directional value measure (DV), the

annualized returns from two different trading strategies generated by our forecasts and risk adjusted performance measures given by the Sharpe ratios for both of the trading strategies.

The directional accuracy measure $DA_{th} = I\left(\text{sgn}(S_t - S_{t-h}) = \text{sgn}(\hat{S}_{t|t-h} - S_{t-h})\right)$, introduced already above, is a binary variable indicating whether the direction of the exchange rate change was correctly forecast at horizon h ($DA_{th} = 1$) or not ($DA_{th} = 0$). While the function DA_{th} is robust to outlying forecasts, it does not consider the size of the realized directional movements. The economic value of directional forecasts is better captured by assigning to each correctly predicted change its magnitude (see Blaskowitz and Herwartz, 2011). The directional value (DV) statistic, defined as $DV_{th} = |S_t - S_{t-h}|DA_{th}$ is used for this purpose.

The performance of exchange rate forecasts based on their profitability is evaluated by constructing simple trading strategies based on the predictions. We start with a simple trading strategy as described in Gencay (1998), where the selling/buying signal is based on the current exchange rate, namely, forecast upward movements of the exchange rate with respect to the actual value (positive returns) are executed as long positions while the forecast downward movements (negative returns) are executed as short positions; i.e., the total return of the trading strategy over n periods is given by

$$R_h^S = \sum_{t=1}^n y_{t-h,h}^S r_{th} = \sum_{t=1}^n R_{th}^S \quad (18)$$

where $r_{th} = \log(S_t/S_{t-h})$, $t = 1, \dots, n$,

$$y_{t-h,h}^S = \begin{cases} -1, & \text{for selling signal (forecast downward movement for horizon } h) \\ & \hat{S}_{t|t-h} < S_{t-h} \\ 1, & \text{for buying signal (forecast upward movement for horizon } h) \\ & \hat{S}_{t|t-h} > S_{t-h} \end{cases}$$

and $R_{th}^S = y_{t-h,h}^S r_{th}$. We label this trading strategy TS^S . While this trading strategy is based on comparing current and predicted exchange rates, a comparison of the forecast with the forward rate would be a natural building block for an alternative trading strategy. The trading strategy used in Boothe (1983), for instance, generates signals based on the comparison of the forecast value to the current forward rate

$$R_h^F = \sum_{t=1}^n y_{t-h,h}^F r_{th} = \sum_{t=1}^n R_{th}^F \quad (19)$$

where

$$y_{t-h,h}^F = \begin{cases} -1, & \hat{S}_{t|t-h} < F_{t|t-h} \\ 1, & \hat{S}_{t|t-h} > F_{t|t-h} \end{cases}$$

$F_{t|t-h}$ is the forward rate for time t given at time $t-h$ and $R_{th}^F = y_{t-h,h}^F r_{th}$. We label this trading strategy TS^F . Returns generated by the trading strategy where the selling/buying signal is based on the current exchange rate, TS^S , are denoted by R^S , and the returns generated by the trading strategy where the selling/buying signal is based on the current forward rate, TS^F , are denoted by R^F .

In addition to the profitability measures presented above, we also perform comparisons based on *Sharpe ratios* - the excess return per unit of deviation generated by a trading strategy; i.e., $SR = \frac{R}{\sigma}$, where R is the (annualized) return of a trading strategy and σ is its standard deviation. The natural benchmark return in the definition of the Sharpe ratio for our application appears to be a zero return, reflecting that the investor does not take any position in the foreign exchange market.

The different performance measures that can be computed based on the forecasts of our macro-econometric models need to be compared with a set of performance measures implied by reference models against which to benchmark the ability of the models entertained. The benchmark model for MAE and MSE measures is the random walk model, for DA and DV measures it is the random walk with an intercept and for trading strategies TS^S and TS^F the following benchmark trading strategies are used (for more details see Neely and Weller, 2013):

- The *buy-and-hold* strategy: $R^{BH} = \log(S_n/S_1)$; i.e., buying at period 1 and holding it at least till period n .
- Trading signals based on the *forward rate*; i.e., whether the forward exchange rate indicates appreciation or depreciation. I.e.,

$$R_h^{Fo} = \sum_{t=1}^n y_{t-h,h}^{Fo} r_{th} \quad (20)$$

where

$$y_{t-h,h}^{Fo} = \begin{cases} -1, & S_{t-h} > F_{t|t-h} \\ 1, & S_{t-h} < F_{t|t-h} \end{cases} \quad (21)$$

- *Moving average rules*, based on $MA_t(m, n) = \frac{1}{m} \sum_{i=1}^{m-1} S_{t-i} - \frac{1}{n} \sum_{i=1}^{n-1} S_{t-i}$ where $m < n$. If $MA_t(m, n) > 0$ then a buying signal is generated and if $MA_t(m, n) < 0$ then a selling signal is generated.⁴ The corresponding return is given by

$$R_h^{MA} = \sum_{t=1}^n y_{t-h,h}^{MA} r_{th} \quad (22)$$

where

$$y_{t-h,h}^{MA} = \begin{cases} -1, & MA_{t-h}(m, n) < 0 \\ 1, & MA_{t-h}(m, n) > 0 \end{cases} \quad (23)$$

For monthly exchange rates and one-step-ahead predictions, the most widely used *MA* rule in the fund management industry is $MA(1, 2)$. For a forecast horizon of h , we generalize the statistic to $MA(h, 2h)$ and build the signals based on this moving average statistic.

- *Filter rules*, where the buy signal is generated when the exchange rate has increased by more than a certain percent above its most recent low and the sell signal is generated when the exchange rate has fallen by more than the same percent from its most recent high. The resulting return is then given by

$$R_h^{Filter} = \sum_{t=1}^n y_{t-h,h}^{Filter} r_{th} \quad (24)$$

where

$$y_{t-h,h}^{Filter} = \begin{cases} -1, & S_{t-h} < S_{t-2h}(1 - x) \\ 1, & S_{t-h} > S_{t-2h}(1 + x) \end{cases} \quad (25)$$

where the filter size x is such that $0 < x < 1$. For our application, $x = 0.01, 0.02$ and 0.1 are used alternatively.

- *Carry trade rules* are based on borrowing in low interest rate currencies to fund investments in high-yield currencies (or target currencies), a strategy implied by the uncovered

⁴See for instance Harris and Yilmaz (2009).

interest rate parity (see Ilut, 2012).⁵ The resulting return is given by

$$R_h^{CT} = \sum_{t=1}^n y_{t-h,h}^{CT} r_{th} \quad (26)$$

where

$$y_{t-h,h}^{CT} = \begin{cases} -1, & i_{t-h,h}^d < i_{t-h,h}^f \\ 1, & i_{t-h,h}^d > i_{t-h,h}^f \end{cases}$$

where $i_{t-h,h}^d$ is a domestic interest rate for h -steps ahead while $i_{t-h,h}^f$ is a foreign interest rate for h -steps ahead.

3 Estimation, prediction and testing for data snooping

3.1 Estimation details

We base our comparison on monthly data spanning the period from January 1980 until December 2013 for the EUR/USD, EUR/GBP, EUR/CHF and EUR/JPY exchange rates. The beginning of the sample is thus $T_0 =$ January 1980, the beginning of the hold-out forecasting sample for individual models used in order to obtain weights based on predictive accuracy is given by $T_1 =$ January 2007. The beginning of the actual out-of-sample forecasting sample is $T_2 =$ January 2010, and the end of the data sample is $T_3 =$ December 2013.⁶

The lag length of the VAR, VEC and DVAR specifications is selected using the AIC criterion for potential lag lengths ranging from 1 to 12 lags.⁷ For the VEC models, selection of the lag length and the number of cointegration relationships is carried out simultaneously using the AIC. Since VAR models are known to forecast poorly due to overfitting (see, e.g., Fair, 1979), we also estimate subset-VAR specifications, where individual parameters of the VAR specification are set equal to zero recursively using t-tests (see Kunst and Neusser, 1986, for a similar approach). While in the set of restricted specifications based on the monetary model which are mentioned in section 2 the parameters are constrained based on theoretical assumptions, in the case of subset-VARs the corresponding specification is estimated and insignificant lags of the

⁵Bekaert et al. (2007) and Krishnakumar and Neto (2012) point out the importance of the link between the interest rate parity and the hypothesis of the term structure for the determination of the exchange rate.

⁶The sources for all variables used are given in the data appendix.

⁷Our results are however robust to model selection using BIC or the HQ criterion.

endogenous variables are removed from the model specification. The restrictions are imposed by setting to zero those parameters for which we cannot reject that they are equal to zero using a one-sided t-test.

In addition to standard VAR, DVAR and VEC models, we also estimate Bayesian VARs. The standard Bayesian approach for estimating VAR models was mainly developed by Doan et al. (1984) and Litterman (1986), who suggest that assuming as a prior that the variables in the VAR follow a random walk would be sensible for economic variables (the Litterman/Minnesota prior). In the case of exchange rates, it would furthermore be consistent with the efficient market hypothesis. We thus estimate DVAR specifications using Bayesian methods, setting the mean of the prior for the estimated coefficients to zero. Regarding the specification of the prior variance-covariance matrix, V , of the coefficients of different lags of the endogenous variables of the model a typical element is set to

$$v_{ij,l} = \begin{cases} (\lambda/l^d)^2 & \text{for } i = j, \\ (\lambda\rho\sigma_i/l^d\sigma_j)^2 & \text{for } i \neq j, \end{cases} \quad (27)$$

where $v_{ij,l}$ is the prior variance of the parameter corresponding to the l -th lag of variable j in equation i , $\lambda > 0$ is the ‘overall tightness’ parameter, d is the rate of decay, and $\rho \in (0, 1)$ allows for differences in the weight of own lags of the explained variable with respect to lags of other variables.⁸

We consider rolling-window estimation for our analysis; i.e., we keep the estimation sample size constant (equal to $T_1 - T_0$) as we re-estimate the models, thus moving the window that defines the sample used to estimate the model parameters. The performance measures for each model, as introduced in section 2.3, are calculated over the out-of-sample period for a given

⁸For our estimation results, we set $\lambda = 0.1$, $\rho = 0.99$, and $d = 1$.

forecasting horizon and aggregated as follows

$$\begin{aligned}
MSE_h &= \sum_{j=0}^{T_3-T_2} MSE_{T_2+j,h} \\
MAE_h &= \sum_{j=0}^{T_3-T_2} MAE_{T_2+j,h} \\
DA_h &= \sum_{j=0}^{T_3-T_2} \frac{DA_{T_2+j,h}}{T_3 - T_2 + 1} \\
DV_h &= \frac{\sum_{j=0}^{T_3-T_2} DV_{T_2+j,h}}{\sum_{j=0}^{T_3-T_2} |S_{T_2+j} - S_{T_2+j-h}|} \\
&= \frac{\sum_{j=0}^{T_3-T_2} |\hat{S}_{T_2+j} - S_{T_2+j-h}| DA_{T_2+j,h}}{\sum_{j=0}^{T_3-T_2} |S_{T_2+j} - S_{T_2+j-h}|}
\end{aligned}$$

where $h = 1, \dots, 12$.

3.2 Data snooping bias free tests for equal predictive ability

In order to assess whether the predictive superiority of certain models is systematic and not due to luck, we also perform bootstrap tests for the comparison of predictive ability with respect to the benchmark models and trading strategies. In particular, we use the ‘reality check’ (RC) test by White (2000), the test for superior predictive ability (SPA) by Hansen (2005), the stepwise test of multiple check (stepM-RC) by Romano and Wolf (2005) and the stepwise multiple superior predictive ability test (stepM-SPA) by Hsu et al. (2010).

The following relative performance measures, d_{ith} , $i = 1, \dots, k$, $t = T_2, T_2 + 1, \dots, T_3$, $h = 1, \dots, 12$ are computed and the tests are defined based on them:

$$d_{ith} = \left\{ \begin{array}{l} MSE_{RW,th} - MSE_{ith} \\ MAE_{RW,th} - MAE_{ith} \\ DA_{ith} - DA_{RW_{int},th} \\ DV_{ith} - DV_{RW_{int},th} \\ y_{ith}^S r_{th} - y_{ref,th} r_{th} \\ y_{ith}^F r_{th} - y_{ref,th} r_{th} \\ SR_{ith}^S - SR_{ith}^{ref} \\ SR_{ith}^F - SR_{ith}^{ref} \end{array} \right. \quad (28)$$

Index *ref* denotes the reference/benchmark trading rule, implying that we concentrate on relative returns. The benchmark trading strategies are defined by (20)–(27). Thus, $ref \in \{Fo, MA, Filter, CT\}$. SR^S stands for the Sharpe ratio implied by the trading strategy TS^S as defined in (18), SR^F stands for the Sharpe ratio implied by the trading strategy TS^F as defined in (19)⁹ and RW_{int} stands for the random walk with an intercept.

White’s (2000) bootstrap RC test is a comprehensive test across all models considered and directly quantifies the effect of data snooping by testing the null hypothesis that the performance of the best model is no better than the performance of the benchmark model.¹⁰ The null hypothesis of the test is

$$H_0 : \mathbb{E}(\mathbf{d}_t) \leq 0 \quad (29)$$

where $\mathbf{d}_t = (d_{1t}, \dots, d_{kt})$ is a k –dimensional vector of relative performance measures as defined in (28). Rejection of (29) implies that at least one model beats the benchmark. The RC test is constructed using the test statistic

$$T_n^{RC} = \max\{\sqrt{n}\bar{d}_1, \dots, \sqrt{n}\bar{d}_k\} \quad (30)$$

where n is the number of out-of-sample observations ($n = T_3 - T_2 + 1$) and $\bar{d}_i = \sum_{t=T_2}^{T_3} d_{it}$ for $i = 1, \dots, k$. Following White (2000), the bootstrap RC p –values are calculated using the stationary bootstrap method of Politis and Romano (1994), where the potential dependence in \mathbf{d}_t is taken into account. At first, the empirical distribution of T_n^{RC*} is obtained, where

$$T_n^{RC*}(b) = \max\{\sqrt{n}(\bar{d}_1(b) - \bar{d}_1), \dots, \sqrt{n}(\bar{d}_k(b) - \bar{d}_k)\} \quad (31)$$

for $b = 1, \dots, B$, where B is the number of bootstrap simulations. The p –values are obtained by comparing T_n^{RC} with the quantiles of the empirical distribution of T_n^{RC*} .¹¹

Hansen (2005) points out that the RC test of White (2000) is too conservative because its null distribution is obtained under the least favorable configuration to the alternative. The RC test may lose power when poor models are included in the group of models under consideration.

⁹To ease the notation, we omit the index h that indicates the forecast horizon in the discussion below.

¹⁰The term ‘model’ is obviously used in a broad sense that includes forecasting rules and methods (like forecast combinations).

¹¹This procedure involves choosing a dependence parameter q that serves to preserve possible time dependence (see White, 2000). We present in our empirical analysis the results for $q=0.9$, which corresponds to a plausibly low persistence level in exchange rate changes. Qualitatively similar results are found for $q=0.5$ and are not reported but are available from the authors upon request. Similar values for the smoothing parameter are used in Gonzalez-Rivera et al. (2004), Qi and Wu (2006) and Yang et al. (2008).

To improve the power of the test, Hansen (2005) proposes the superior predictive ability (SPA) test. The null hypothesis of the SPA test is the same as in the in White’s RC test, but Hansen (2005) uses the studentized test statistic to improve the power.¹² The test statistic for the SPA test is

$$T_n^{SPA} = \max \left[\max \left\{ \frac{\sqrt{n}\bar{d}_1}{\hat{s}_1}, \dots, \frac{\sqrt{n}\bar{d}_k}{\hat{s}_k} \right\}, 0 \right] \quad (32)$$

where \hat{s}_i is a consistent estimator of $var(\sqrt{n}\bar{d}_i)$, $i = 1, \dots, k$. The same bootstrap method of Politis and Romano (1994) is used to calculate the empirical distribution of the statistic under the null.

One drawback of both RC and SPA tests is that they do not aim at explicitly identifying the models which outperforms the benchmark. Romano and Wolf (2005) propose the stepM-RC test that can identify also those models for which $\mathbb{E}(d_{it}) > 0$ holds. For a given model i , ($i = 1, \dots$) the following individual testing problems are considered

$$H_0^i : \mathbb{E}(d_{it} \leq 0) \quad \text{vs} \quad H_A^i : \mathbb{E}(d_{it} > 0) \quad (33)$$

This multiple testing method yields a decision for each individual testing problem (by either rejecting H_0^i or not). The individual decisions are made such that the familywise error rate¹³ is asymptotically achieved at the significance level α which is achieved by constructing a joint confidence region with a nominal joint coverage probability of $1 - \alpha$. This stepwise procedure is implemented as follows. Without loss of generality we assume that $\{\bar{d}_i\}_{i=1}^k$ are arranged in a descending order. Top j_1 null hypotheses are rejected (i.e., top j_1 models outperform the benchmark) if $\sqrt{n}\bar{d}_l$, $l = 1, \dots, j_1$ is greater than the bootstrapped critical value computed from the bootstrap procedure as in the RC test. If none of the null hypotheses is rejected, the procedure terminates. Otherwise, d_{1t}, \dots, d_{j_1t} , $t = T_2, \dots, T_3$ are removed from the data and the bootstrap simulation is applied to the rest of the data to obtain the new critical value. If $\sqrt{n}\bar{d}_l$, $l = 1, \dots, j_2$ is greater than the new bootstrapped critical value then the following j_2 null hypotheses are rejected. The procedure continues until no more null hypotheses are rejected. In our analysis we use significance levels of 5% and 10%.

Hsu et al. (2010) extend the SPA of Hansen (2005) to a stepwise SPA test in the way Romano and Wolf (2005) did it for the RC test. They show analytically that the stepM-SPA

¹²The improvement of the power of the SPA test over the RC test is confirmed by simulations in Hansen (2005).

¹³The familywise error rate is defined as the probability of rejecting at least one true null hypothesis. For more details, see Romano and Wolf (2005).

test is more powerful than stepM-RC test. The step wise procedure is the same as in the stepM-RC test but with RC test statistics replaced by PCA test statistics.

4 Results

Table 1 presents the abbreviations of the models, forecast combination techniques and benchmark trading strategies used in the analysis. Tables 2 to 9 presents the results of the analysis for each exchange rate, theoretical framework (monetary versus capital flows) and three different prediction horizons (one, six and twelve months ahead). The tables are structured in three blocks, each one corresponding to a different forecasting horizon. Each block, in turn, is divided into three different parts. The top part of the block presents the results for those individual specifications which perform best according to the criteria described in section 2.2 and section 2.3. In the central part of the block, we present the results for all forecast combination methods used. The bottom part of each block, in turn, presents the corresponding measures for the best-performing benchmark strategies. The forecasts are evaluated using the loss and profit measures described in section 2.3¹⁴ and the predictive superiority of the models which perform better than the benchmark is assessed by means of the bootstrap stepM-SPA test by Hsu et al. (2010).¹⁵

[Include Table 1 about here]

Tables 2 and 3 report the predictive ability measures of the monetary and capital flows models as well as combinations thereof for the EUR/USD exchange rate. The random walk model is always beaten by the best single individual model and the best combination of forecast for 1-step and 6-steps ahead in terms of predictive ability as measured by MAE, MSE, DA and DV (except for the best single individual model for MAE and MSE and 6-steps ahead). The results are slightly different for measures based on 12-steps ahead forecasts. Here, the random walk prevails over the other models for MAE and MSE. However, according to the stepM-SPA test, only the differences in forecasting ability in terms of DA and DV appear significant, while those measured by MAE and MSE measures are all insignificant. More specifically, we find for DA and DV measures that their benchmark random walk model is systematically beaten by the combination of forecasts based on the principal components for 6-steps and 12-steps ahead, which appears superior at the 5% significance level using the stepM-SPA test. Furthermore,

¹⁴The loss measures are based on currency units. Note that returns generated by trading strategies are calculated from the position of a foreign investor.

¹⁵We used all the tests described in section 3.2, but report only the results for the stepM-SPA test in the tables. Detailed results using the other tests are available from the authors upon request.

some capital flows models perform significantly better than the random walk for 1-step ahead in terms of the DA and DV measures. Comparable results for directional forecast are found in Yang et al. (2008) and Dal Bianco et al. (2012). In particular, Yang et al. (2008) point at the forecast superiority of alternative specifications when using weekly data, whereas only one model significantly outperforms the random walk when using daily data. Using weekly data, Dal Bianco et al. (2012), who propose a fundamentals-based econometric model for the weekly changes in the EUR/USD rate with the distinctive feature of mixing economic variables quoted at different frequencies, find that their model significantly outperforms the random walk model for long horizons.

[Include Tables 2 & 3 about here]

As for the performance of trading strategies based on the exchange rate forecasts, the results show that only the returns from trading strategy TS^F implied by the principal components based forecasts combination method is significantly better than the best benchmark models at a 10% significance level. This occurs for 6-steps and 12-steps ahead in the case of the monetary model (see Table 2) and only for 6-steps ahead for the capital flows model. Looking at the Sharpe ratios of returns generated by trading strategies TS^S and TS^F , a slightly stronger evidence of risk adjusted profitability is found (in some cases the results are significant at 5% level). More specifically, forecasts based on principal components are significantly better than the benchmark models, carry trade and MA(12,24), for 6-steps and 12-steps ahead for both the monetary and capital flows models. However, the Sharpe ratio takes values lower than unity, and it has been argued that market practitioners in the foreign exchange market may be not interested in a currency investment strategy that yields a Sharpe ratio less than unity (see Sarno et al., 2006). It should be however noticed that the difference in performance of the other alternative forecasting models with respect to the benchmark model is insignificant.

[Include Tables 4 & 5 about here]

Tables 4 and 5 depict the results for the forecasts of the EUR/GBP exchange rate. These show that several individual forecasting models and combinations of forecast outperform the random walk for DA and DV measures in 1-step and 12-steps ahead predictions, whereas results turn to be all insignificant for MAE and MSE measures. In particular, we find that the forecast combination based on OLS method and principal components outperform the random walk for 1-step ahead at 5% and 10% level, depending on the directional forecast measure considered (see Tables 4 and 5), and three individual models (r-VAR, s-VAR and rs-VAR) along with

the forecast combination based on principal components yield the best performance for 12-steps ahead. For 6-steps ahead, findings show no significant forecast superiority beyond the benchmark specifications. On the whole, these findings contrast with those in Yang et al. (2008) who report evidence of no significant predictability in terms of average directional accuracy for all the forecasting models. As for the trading strategies, results reveal no systematic significant superiority of the models and combinations entertained except for the forecast combinations based on principal components and BMA for 6-steps ahead in the theoretical context of the monetary model for both profit and risk adjusted profit measures generated by the trading strategy TS^F . Quantitatively, the combination of forecast based on principal components yields the best performance. The benchmark model, based on the forward rate, achieves negative returns. By and large, the results for the EUR/USD exchange rate are slightly better in terms of profitability than those for the EUR/GBP, but low values for the Sharpe ratio do not trigger much confidence in obtaining successful investments for potential investors.

[Include Tables 6 & 7 about here]

Tables 6 and 7 contain the results based on forecasts of the EUR/CHF exchange rate. The findings show that none of the models and combinations used outperform the benchmark (random walk) model for 1-step and 6-steps ahead for MAE and MSE measures. Surprisingly, forecasts from some individual forecasting models (DVAR, s-DVAR, r-DVAR and BDVAR) and two combinations of forecast (NEHSR and BMA) outperform the random walk for 12-steps ahead for MAE and MSE measures. As for the predictability measured by the DA and DV criteria, none of the forecasting methods is significantly superior to the benchmark model. These results can be consistent with the heavy interventions of the Swiss central bank in the foreign exchange market documented during the crisis (see e.g. Bordo et al., 2012), which are likely to have affected the information content of macroeconomic fundamentals as a leading indicator of exchange rate changes. The forecast ability of specifications and combinations for both the monetary and the capital flows models is not significantly better than the benchmarks when looking at returns implied by trading strategies TS^S and TS^F and their Sharpe ratios.

[Include Tables 8 & 9 about here]

The results of the prediction exercise for the EUR/JPY exchange rate, as reported in Tables 8 and 9, are marked by the widespread lack of evidence of statistical superiority against the benchmark strategies. Only for the 1-step ahead in the case of DA and DV do we find a general improvement through the use of econometric specifications based on the monetary

model. These results are in line with those in Yang et al. (2008) and emphasize the difficulty of building successful trading strategies based on EUR/JPY predictions. In spite of the large improvements in directional forecasts obtained through the use of econometric specifications and combinations of forecasts in the short run (see for example the results presented in Table 8 for the 1-step ahead horizon), these do not translate to a significant superiority in terms of Sharpe ratios, where strategies based on random walk predictions, carry trade or moving averages are not systematically outperformed by the set of entertained specifications. As in the case of the results for EUR/CHF, the frequency and size of the foreign exchange market interventions of the monetary policy authority in Japan (see e.g. Chortareas et al., 2013) are likely to play an important role in terms of affecting the predictive content of macroeconomic fundamentals for the exchange rate.

Summing up the results across exchange rates and theoretical settings, several general conclusions can be drawn. First of all, there is no evidence of a “*one size fits all*” approach to the specification of single multivariate time series models for exchange rate forecasting which leads to systematically good predictive ability in terms of trading strategies. The use of error correction specifications or Bayesian VAR models does not ensure a lower loss or a higher profit, and there is no systematic relationship between the use of variables related to a particular theoretical setting (monetary or capital flows) and improvements in the predictive ability of the model as measured by our loss and profit measures.

As compared to individual specifications and benchmark strategies, the use of forecast combination methods tends to lead to improvements in the performance of trading rules implied by our forecasts. In particular, forecast pooling based on principal components methods appears to be the most robust technique for the EUR/USD and EUR/GBP. On the other hand, the forecasts for the EUR/CHF exchange rate based on both individual models and forecast combinations (namely the Bayesian model averaging method) do outperform the random walk model for a long-term prediction horizon. As for the EUR/JPY exchange rate, the performance of the forecasts obtained with macroeconometric models and their combinations does not robustly improve over the standard benchmarks. This result supports the view that predicting exchange rates using macroeconomic variables is a particularly difficult task in foreign exchange markets where monetary policy interventions are frequent and sizeable. Such a result is in line, for instance, with the work of Beine et al. (2007), Neely (2008) or Miyajima (2013), who find that interventions increase the volatility of exchange rates and exchange rate forecasts.

In spite of the improvements in profit measures obtained by combinations of predictions for EUR/USD and EUR/GBP, the results concerning differences in Sharpe ratios of returns given by the trading strategies indicate that the margin for achieving systematic monetary profits

in the foreign exchange market using macroeconomic models is very limited and that the answer to the question posed by the title of this paper is very likely to be “*Unfortunately, no*”.

5 Conclusions

Using a large battery of multivariate time series models and forecast combination methods, we provide a systematic comparison of out-of-sample forecast accuracy in terms of loss and profit measures for the EUR/USD, EUR/GBP, EUR/CHF and EUR/JPY exchange rates. The contributions of this study are twofold. First, we use recently developed directional forecast accuracy measures that account for both the direction and the size of the changes in exchange rates and are robust to outliers. These measures provide an economically interpretable loss/success functional framework in a decision-theoretical context. Second, we exploit the potential of a large number of forecast combination methods for both forecast accuracy evaluation and profitability. In doing so, we propose a new method of forecast combination based on the economic evaluation of directional predictions. Our empirical results emphasize the lack of superiority of a single specification or forecast combination technique over different prediction horizons and exchange rates. The results for EUR/USD and the EUR/GBP, forecast combinations based on principal component decompositions of individual model predictions appear particularly promising in improving profitability based performance, albeit not systematically superior to the benchmarks across forecasting horizons. The forecasts for the EUR/CHF exchange rate based on both individual models and forecast combinations outperform the random walk model for a long-term prediction horizon. Finally, for the EUR/JPY exchange rate the results are not supportive of any of the methods entertained and highlight the superiority of simple trading rules in terms of profitability.

Future research will extend this study by considering optimal currency portfolios based on a variety of foreign exchange trading strategies and their impact on different (risk adjusted) profit measures. It will investigate whether the portfolios based on the trading strategies implied by the exchange rate forecasts may have better performance than the portfolios based on the technical trading rules strategies which do not use forecasts. As for the forecasts of the exchange rate, both individual models and combinations of the forecasts will be used.

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Appendix: Data description and sources

All time series have monthly periodicity (January 1980 to December 2013), and have been extracted from Thomson Financial Datastream. The variables used for EU-11, Japan, Switzerland, UK and USA, are:

- Money supply: M1 aggregate, indexed 1990:1=100. Seasonally unadjusted.
- Output: Industrial production index 1990:1=100.
- Short term interest rate: 3-month interbank offered rate.
- Long term interest rate: 10-year rate interest rate on government bonds
- leading indicator for Germany as a proxy for Europe: IFO index
- leading indicator for Japan: Leading diffusion index from Cabinet Office
- leading indicator for Switzerland: KOF economic barometer
- leading indicator for UK: CBI output volume index
- leading indicator for US: ISM index
- Stock market indices covering at least 80% of market capitalization in the respective country.

Table 1: Models, combination methods and benchmarks

Abbreviations	Description
	Individual models
VAR(p)	Vector autoregression in levels based on domestic and foreign variables with p lags
DVAR(p)	Vector autoregression in first differences based on domestic and foreign variables with p lags
VEC(c,p)	Vector error correction model based on domestic and foreign variables with c cointegration relationships
r-VAR(p)	Restricted VAR, based on differences between domestic and foreign variables
r-DVAR(p)	Restricted DVAR, based on differences between domestic and foreign variables
r-VEC(c,p)	Restricted VEC, based on differences between domestic and foreign variables with c cointegration relationships
s-VAR(p)	Subset vector autoregression in levels based on domestic and foreign variables with p lags
s-DVAR(p)	Subset vector autoregression in first differences based on domestic and foreign variables with p lags
rs-VAR(p)	Restricted subset VAR, based on differences between domestic and foreign variables
rs-DVAR(p)	Restricted subset DVAR, based on differences between domestic and foreign variables
BDVAR(p)	Bayesian vector autoregression in first differences based on domestic and foreign variables
r-BDVAR(p)	Bayesian vector autoregression in first differences based on differences between domestic and foreign variables
	Forecast combination methods
mean	Forecasting combination based on mean of individual predictions
tmean	Forecasting combination based on trimmed mean of individual predictions
median	Forecasting combination based on median of individual predictions
OLS	Forecasting combination based on pooling using OLS
PC	Forecasting combination based on principal components
DMSFE	Forecasting combination based on discounted mean square forecast errors
HR	Forecasting combination based on hit rates
EHR	Forecasting combination based on exponential of hit rates
EEDF	Forecasting combination based on the economic evaluation of directional forecasts
BMA	Forecasting combination based on Bayesian model averaging weights using the predictive likelihood
FMA-aic	Forecasting combination based on AIC weights
FMA-bic	Forecasting combination based on BIC weights
FMA-hq	Forecasting combination based on Hannan-Quinn weights
	Benchmarks
RW	Random walk model (for MAE and MSE)
RW _{int}	Random walk model with intercept (for DA and DV)
BH	Buy-and-hold trading strategy (for TS ^S and TS ^F)
Forward rate	Rule based on the forward rate (for TS ^S and TS ^F)
MA(m, n)	Rule based on differences between moving averages over m and n periods (for TS ^S and TS ^F)
Filter	Filter rule based trading strategy (for TS ^S and TS ^F)
CT	Carry trade rule (for TS ^S and TS ^F)

Table 2: Forecasts of the monetary model for the EUR/USD exchange rate

Model	MAE	MSE	DA	DV	R ^S	R ^F	SR ^S	SR ^F
1-step								
r-VAR(12)	0.712	0.016	60.417	68.887	8.672	7.481	0.313	0.266
rs-VAR(2)	0.678	0.015	60.417	67.735	8.046	4.755	0.288	0.166
mean	0.712	0.016	54.167	62.856	5.751	3.801	0.202	0.132
tmean	0.710	0.016	54.167	60.016	4.490	3.801	0.156	0.132
median	0.690	0.015	58.333	63.627	6.066	4.755	0.213	0.166
OLS	0.769	0.019	52.083	59.360	4.267	3.177	0.148	0.110
PC	0.684	0.016	45.833	52.047	1.130	5.544	0.039	0.194
DMSFE	0.706	0.016	54.167	60.016	4.490	3.801	0.156	0.132
HR	0.712	0.016	54.167	62.856	5.751	3.801	0.202	0.132
EHR	0.732	0.018	50.000	52.306	0.892	6.643	0.031	0.235
EEDF	0.713	0.016	54.167	62.856	5.751	3.801	0.202	0.132
BMA	0.793	0.021	47.917	54.906	2.056	6.643	0.071	0.235
FMA-aic	0.755	0.019	45.833	47.117	-1.405	6.103	-0.048	0.215
FMA-bic	0.716	0.017	58.333	67.405	7.771	3.243	0.278	0.112
FMA-hq	0.733	0.017	52.083	61.683	5.195	3.801	0.182	0.132
RW	0.686	0.016	47.917	46.675				
MA(1,2)					6.893	6.893	0.244	0.244
6-steps								
r-VAR(12)	2.556	0.192	50.000	61.837	2.713	2.140	0.210	0.164
r-VEC(2,11)	2.617	0.206	52.083	60.650	2.360	-0.136	0.182	-0.010
s-DVAR(1)	1.955	0.122	45.833	42.485	-1.574	-1.156	-0.12	-0.088
rs-VAR(2)	1.990	0.117	52.083	62.135	2.666	0.955	0.206	0.073
mean	2.136	0.138	35.417	36.835	-2.796	-0.998	-0.217	-0.076
tmean	2.119	0.137	37.500	39.890	-2.168	-1.072	-0.166	-0.081
median	1.998	0.124	37.500	39.879	-2.191	-1.046	-0.168	-0.079
OLS	2.822	0.255	43.750	45.732	-0.829	-1.403	-0.063	-0.107
PC	1.896	0.109	72.917	80.388	6.601	<i>7.024</i>	<i>0.579</i>	<i>0.631</i>
DMSFE	2.103	0.134	33.333	36.727	-2.818	-1.095	-0.219	-0.083
HR	2.168	0.142	41.667	46.645	-0.696	-0.998	-0.053	-0.076
EHR	3.112	0.284	45.833	54.930	1.010	0.041	0.077	0.003
EEDF	2.181	0.144	37.500	39.815	-2.184	-0.998	-0.168	-0.076
BMA	2.743	0.224	41.667	45.052	-1.098	-1.481	-0.083	-0.113
FMA-aic	2.398	0.177	47.917	53.282	0.689	0.009	0.052	0.001
FMA-bic	2.033	0.131	45.833	46.471	-0.813	-0.628	-0.062	-0.048
FMA-hq	2.174	0.150	43.750	43.262	-1.464	-0.845	-0.112	-0.064
RW	1.916	0.113	50.000	41.065				
CT					4.116	4.116	0.328	0.328
12-steps								
r-VAR(12)	3.660	0.433	50.000	64.691	1.943	1.133	0.254	0.145
rs-VAR(2)	2.622	0.191	56.25	61.821	<i>1.583</i>	0.509	0.205	0.065
r-BDVAR(4)	2.487	0.188	39.583	32.598	-2.311	-3.075	-0.306	-0.423
mean	3.027	0.255	33.333	36.021	-1.820	-2.074	-0.237	-0.272
tmean	2.951	0.240	35.417	38.385	-1.525	-1.84	-0.197	-0.239
median	2.670	0.193	37.500	38.612	-1.522	-1.635	-0.196	-0.211
OLS	9.012	6.963	52.083	58.318	1.098	1.107	0.140	0.141
PC	2.414	0.172	72.917	83.300	4.379	<i>4.406</i>	<i>0.669</i>	0.674
DMSFE	3.061	0.259	33.333	36.021	-1.820	-2.498	-0.237	-0.333
HR	3.139	0.275	33.333	36.021	-1.820	-2.369	-0.237	-0.314
EHR	4.130	0.491	25.000	25.093	-3.250	-3.310	-0.452	-0.462
EEDF	3.179	0.284	33.333	36.021	-1.820	-2.378	-0.237	-0.316
BMA	3.737	0.443	37.500	41.591	-1.099	-1.629	-0.140	-0.211
FMA-aic	3.408	0.355	39.583	44.390	-0.745	-1.347	-0.095	-0.173
FMA-bic	2.805	0.224	41.667	38.670	-1.506	-2.340	-0.194	-0.310
FMA-hq	3.129	0.284	41.667	44.201	-0.796	-1.551	-0.101	-0.200
RW	2.330	0.163	43.750	41.265				
MA(12,14)					2.335	2.335	0.310	0.310

See Table 1 for the abbreviation of the models. Underlined **bold** figures indicate that the null hypothesis that the model does not outperform the benchmark model is rejected at the 5% significance level and underlined *italic* figures indicate that the null hypothesis is rejected at the 10% significance level using the stepM-SPA test. The stepM-SPA test is performed setting the dependence parameter q equal to 0.9 and the number of bootstrap simulations is equal to 5000. Both MAE and MSE loss measures are reported in exchange rate levels.

Table 3: Forecasts of the capital flows model for the EUR/USD exchange rate

Model	MAE	MSE	DA	DV	R ^S	R ^F	SR ^S	SR ^F
1-step								
r-DVAR(11)	0.729	0.017	54.167	62.952	5.817	10.163	0.204	0.374
rs-DVAR(1)	0.652	0.015	<u>66.667</u>	<u>70.078</u>	9.149	4.719	0.332	0.165
r-BDVAR(4)	0.662	0.015	<u>66.667</u>	<u>71.955</u>	10.026	4.755	0.368	0.166
mean	0.686	0.016	56.250	56.644	3.063	10.163	0.106	0.374
tmean	0.685	0.016	56.250	56.644	3.063	10.163	0.106	0.374
median	0.684	0.016	60.417	60.497	4.835	7.861	0.169	0.281
OLS	0.870	0.027	47.917	47.895	-1.055	6.737	-0.036	0.238
PC	0.657	0.015	54.167	57.24	3.435	8.076	0.119	0.289
DMSFE	0.677	0.015	56.250	56.644	3.063	10.163	0.106	0.374
HR	0.684	0.016	56.250	56.644	3.063	10.163	0.106	0.374
EHR	0.678	0.015	<u>66.667</u>	<u>75.064</u>	11.365	7.597	0.425	0.271
EEDF	0.685	0.016	56.250	56.644	3.063	10.163	0.106	0.374
BMA	0.790	0.021	<u>62.500</u>	59.263	4.221	8.487	0.147	0.305
FMA-aic	0.727	0.018	60.417	58.135	3.743	7.792	0.130	0.278
FMA-bic	0.679	0.016	58.333	56.500	3.092	4.755	0.107	0.166
FMA-hq	0.679	0.016	58.333	59.368	4.327	8.155	0.151	0.292
RW	0.686	0.016	47.917	46.675				
MA(1,2)					6.893	6.893	0.244	0.244
6-steps								
rs-VAR(2)	2.035	0.128	54.167	62.143	2.689	2.318	0.208	0.178
rs-DVAR(1)	1.949	0.122	54.167	52.331	0.428	-0.349	0.032	-0.026
r-BDVAR(4)	1.951	0.121	52.083	48.323	-0.428	1.570	-0.032	0.12
mean	2.062	0.137	47.917	46.624	-0.715	-0.358	-0.054	-0.027
tmean	2.083	0.138	45.833	45.969	-0.853	-0.832	-0.065	-0.063
median	2.110	0.136	45.833	45.969	-0.853	-1.090	-0.065	-0.083
OLS	2.618	0.252	47.917	48.809	-0.115	0.479	-0.009	0.036
PC	1.813	0.101	<u>75.000</u>	<u>81.840</u>	6.930	<u>7.137</u>	<u>0.619</u>	<u>0.645</u>
DMSFE	2.035	0.133	45.833	43.644	-1.327	-0.648	-0.101	-0.049
HR	2.071	0.137	47.917	46.624	-0.715	-0.648	-0.054	-0.049
EHR	2.302	0.150	37.500	46.734	-0.552	0.037	-0.042	0.003
EEDF	2.087	0.139	47.917	46.624	-0.715	-0.358	-0.054	-0.027
BMA	3.048	0.261	43.750	43.655	-1.344	-0.950	-0.102	-0.072
FMA-aic	2.464	0.183	43.750	45.865	-0.875	-0.868	-0.066	-0.066
FMA-bic	1.970	0.125	41.667	41.620	-1.788	0.649	-0.137	0.049
FMA-hq	2.069	0.138	39.583	40.221	-2.088	-0.363	-0.160	-0.028
RW	1.916	0.113	50.000	41.065				
CT					4.116	4.116	0.328	0.328
12-steps								
DVAR(12)	3.216	0.269	45.833	59.200	1.248	0.761	0.160	0.097
rs-VAR(2)	2.850	0.246	56.250	58.735	1.180	1.845	0.151	0.240
r-BDVAR(4)	2.464	0.186	39.583	32.598	-2.311	-1.971	-0.306	-0.258
mean	2.659	0.197	45.833	49.934	0.052	-0.618	0.007	-0.078
tmean	2.683	0.199	39.583	45.645	-0.516	-1.259	-0.065	-0.161
median	2.653	0.199	31.250	33.107	-2.178	-1.514	-0.287	-0.195
OLS	6.391	2.746	54.167	49.094	-0.181	-0.267	-0.023	-0.034
PC	2.474	0.170	<u>77.083</u>	<u>82.969</u>	4.324	4.370	<u>0.656</u>	<u>0.666</u>
DMSFE	2.616	0.193	45.833	49.934	0.052	-1.009	0.007	-0.129
HR	2.684	0.201	45.833	49.934	0.052	-0.618	0.007	-0.078
EHR	2.781	0.221	50.000	61.439	1.545	-0.978	0.199	-0.125
EEDF	2.689	0.202	45.833	49.934	0.052	-0.618	0.007	-0.078
BMA	3.983	0.431	35.417	41.152	-1.096	-2.702	-0.140	-0.364
FMA-aic	3.229	0.284	33.333	35.863	-1.795	-2.411	-0.233	-0.321
FMA-bic	2.522	0.191	37.500	32.177	-2.352	-1.184	-0.312	-0.152
FMA-hq	2.736	0.212	35.417	36.085	-1.804	-2.083	-0.235	-0.273
RW	2.330	0.163	43.750	41.265				
MA(12,24)					2.335	2.335	0.310	0.310

See Table 1 for the abbreviation of the models. Underlined **bold** figures indicate that the null hypothesis that the model does not outperform the benchmark model is rejected at the 5% significance level and underlined *italic* figures indicate that the null hypothesis is rejected at the 10% significance level using the stepM-SPA test. The stepM-SPA test is performed setting the dependence parameter q equal to 0.9 and the number of bootstrap simulations is equal to 5000. Both MAE and MSE loss measures are reported in exchange rate levels.

Table 4: Forecasts of the monetary model for the EUR/GBP exchange rate

Model	MAE	MSE	DA	DV	R ^S	R ^F	SR ^S	SR ^F
1-step								
r-BDVAR(2)	0.743	0.017	<u>56.250</u>	<u>65.490</u>	4.831	4.602	0.248	0.235
mean	0.762	0.018	50.000	56.698	2.046	3.279	0.102	0.166
tmean	0.762	0.018	52.083	57.435	2.286	3.488	0.115	0.176
median	0.765	0.018	52.083	57.435	2.286	3.279	0.115	0.166
OLS	0.923	0.037	<u>58.323</u>	56.26	1.897	3.300	0.095	0.167
PC	0.717	0.017	<u>56.250</u>	63.221	4.163	2.057	0.212	0.103
DMSFE	0.762	0.018	50.000	56.698	2.046	3.279	0.102	0.166
HR	0.761	0.018	50.000	56.698	2.046	3.279	0.102	0.166
EHR	0.756	0.018	50.000	56.698	2.046	3.488	0.102	0.176
EEDF	0.761	0.018	50.000	56.698	2.046	3.279	0.102	0.166
BMA	0.754	0.018	54.167	61.178	3.400	4.602	0.172	0.235
FMA-aic	0.773	0.018	47.917	53.682	1.067	3.279	0.053	0.166
FMA-bic	0.771	0.018	50.000	55.138	1.545	4.014	0.077	0.204
FMA-hq	0.772	0.018	47.917	53.682	1.067	3.279	0.053	0.166
RW	0.747	0.018	37.500	44.459				
CT					2.647	2.647	0.133	0.133
6-steps								
rs-DVAR(1)	2.021	0.121	60.417	57.300	1.004	2.274	0.117	<u>0.273</u>
mean	2.214	0.139	45.833	50.908	0.130	-0.070	0.015	-0.008
tmean	2.218	0.14	43.750	46.232	-0.558	-0.070	-0.065	-0.008
median	2.257	0.146	43.750	43.745	-0.892	0.176	-0.104	0.020
OLS	3.863	0.566	47.917	38.710	-1.550	-0.283	-0.182	-0.033
PC	1.883	0.106	60.417	62.368	1.811	<u>2.660</u>	0.214	<u>0.323</u>
DMSFE	2.217	0.140	45.833	50.908	0.130	-0.070	0.015	-0.008
HR	2.223	0.141	45.833	50.908	0.130	-0.070	0.015	-0.008
EHR	2.532	0.184	41.667	47.781	-0.313	-1.528	-0.036	-0.179
EEDF	2.236	0.142	45.833	50.908	0.130	-0.448	0.015	-0.052
BMA	2.021	0.121	60.417	57.300	1.004	2.274	0.117	<u>0.273</u>
FMA-aic	2.266	0.146	45.833	50.908	0.130	-0.229	0.015	-0.027
FMA-bic	2.218	0.141	43.750	43.751	-0.892	0.118	-0.104	0.014
FMA-hq	2.246	0.144	43.750	46.232	-0.558	-0.070	-0.065	-0.008
RW	2.046	0.124	45.833	42.113				
Forward rate					-1.453	-1.453	-0.17	-0.17
12-steps								
VAR(2)	3.340	0.399	54.167	48.290	-0.155	0.452	-0.029	0.084
r-VAR(2)	2.881	0.334	62.500	54.921	0.474	0.123	0.088	0.023
s-VAR(2)	3.419	0.430	<u>56.250</u>	<u>49.965</u>	0.008	0.452	0.002	0.084
rs-VAR(2)	2.896	0.337	62.500	54.921	0.474	0.123	0.088	0.023
mean	2.614	0.242	52.083	46.165	-0.367	0.021	-0.068	0.004
tmean	2.640	0.242	54.167	48.934	-0.112	-0.705	-0.021	-0.132
median	2.808	0.258	41.667	38.170	-1.121	-0.967	-0.213	-0.182
OLS	8.240	2.677	37.500	33.624	-1.453	-1.300	-0.280	-0.249
PC	2.099	0.161	60.417	<u>53.818</u>	0.367	1.541	0.068	0.299
DMSFE	2.646	0.244	54.167	48.934	-0.112	-0.352	-0.021	-0.065
HR	2.640	0.250	54.167	47.833	-0.207	0.021	-0.038	0.004
EHR	3.146	0.350	50.000	43.850	-0.579	0.271	-0.108	0.050
EEDF	2.618	0.242	54.167	47.833	-0.207	0.021	-0.038	0.004
BMA	2.838	0.230	39.583	38.106	-1.122	-0.817	-0.213	-0.153
FMA-aic	2.703	0.254	54.167	48.934	-0.112	-0.352	-0.021	-0.065
FMA-bic	2.715	0.246	52.083	46.362	-0.355	-0.933	-0.066	-0.176
FMA-hq	2.706	0.250	54.167	48.934	-0.112	-0.512	-0.021	-0.095
RW	2.597	0.193	39.583	37.279				
CT					1.203	1.203	0.229	0.229

See Table 1 for the abbreviation of the models. Underlined **bold** figures indicate that the null hypothesis that the model does not outperform the benchmark model is rejected at the 5% significance level and underlined *italic* figures indicate that the null hypothesis is rejected at the 10% significance level using the stepM-SPA test. The stepM-SPA test is performed setting the dependence parameter q equal to 0.9 and the number of bootstrap simulations is equal to 5000. Both MAE and MSE loss measures are reported in exchange rate levels.

Table 5: Forecasts of the capital flows model for the EUR/GBP exchange rate

Model	MAE	MSE	DA	DV	R ^S	R ^F	SR ^S	SR ^F
1-step								
r-VEC(2,11)	0.771	0.020	58.333	63.603	4.169	3.293	0.212	0.166
rs-DVAR(1)	0.767	0.019	56.250	61.328	3.447	5.577	0.174	0.289
r-BDVAR(2)	0.755	0.018	56.250	61.328	3.447	4.842	0.174	0.249
mean	0.769	0.018	52.083	54.182	1.219	2.792	0.061	0.140
tmean	0.770	0.018	52.083	54.182	1.219	2.792	0.061	0.140
median	0.765	0.018	50.000	58.395	2.535	4.223	0.127	0.215
OLS	0.998	0.038	<u>64.583</u>	<i>70.682</i>	6.659	7.716	0.352	0.417
PC	0.731	0.017	<u>62.500</u>	65.624	4.914	4.261	0.252	0.217
DMSFE	0.770	0.018	52.083	54.182	1.219	2.792	0.061	0.140
HR	0.770	0.018	52.083	54.182	1.219	2.792	0.061	0.140
EHR	0.771	0.018	52.083	57.783	2.301	4.734	0.115	0.243
EEDF	0.770	0.018	52.083	54.182	1.219	2.792	0.061	0.140
BMA	0.767	0.019	56.250	61.328	3.447	5.577	0.174	0.289
FMA-aic	0.779	0.019	50.000	56.754	2.024	4.223	0.101	0.215
FMA-bic	0.779	0.019	47.917	54.522	1.296	4.223	0.065	0.215
FMA-hq	0.779	0.019	47.917	54.908	1.415	4.223	0.071	0.215
RW	0.747	0.018	37.500	44.459				
CT					2.647	2.647	0.133	0.133
6-steps								
DVAR(3)	2.161	0.132	52.083	57.764	1.056	2.355	0.123	0.283
rsDVAR(1)	2.018	0.120	58.333	56.977	0.960	1.339	0.112	0.157
mean	2.264	0.145	54.167	51.152	0.198	0.548	0.023	0.063
tmean	2.230	0.141	50.000	46.073	-0.541	0.979	-0.063	0.114
median	2.149	0.133	54.167	50.139	0.060	1.439	0.007	0.169
OLS	3.659	0.455	54.167	44.362	-0.849	-1.066	-0.098	-0.124
PC	1.964	0.108	56.250	58.709	1.283	1.787	0.150	0.211
DMSFE	2.264	0.144	52.083	48.499	-0.171	0.646	-0.020	0.075
HR	2.285	0.147	47.917	45.034	-0.678	0.548	-0.079	0.063
NESHR	2.441	0.172	47.917	43.351	-0.919	-0.115	-0.107	-0.013
EEFF	2.298	0.149	47.917	44.945	-0.698	0.548	-0.081	0.063
BMA	2.018	0.120	58.333	56.977	0.960	1.339	0.112	0.157
FMA-aic	2.280	0.145	52.083	50.738	0.124	0.700	0.014	0.081
FMA-bic	2.289	0.147	45.833	46.794	-0.449	0.849	-0.052	0.099
FMA-hq	2.284	0.146	50.000	48.141	-0.261	0.849	-0.030	0.099
RW	2.046	0.124	45.833	42.113				
Forward rate					-1.453	-1.453	-0.17	-0.17
12-steps								
rs- <u>VAR</u> (2)	2.629	0.229	<u>58.333</u>	<u>52.261</u>	0.213	-0.310	0.040	-0.058
r-BDVAR(2)	2.756	0.219	39.583	37.629	-1.177	-0.415	-0.224	-0.077
mean	2.871	0.273	45.833	38.509	-1.015	-1.701	-0.192	-0.333
tmean	2.846	0.264	47.917	40.059	-0.875	-1.171	-0.164	-0.223
median	2.835	0.253	37.500	31.666	-1.668	-0.762	-0.325	-0.143
OLS	12.622	38.375	20.833	15.648	-3.136	-3.136	-0.718	-0.718
PC	2.068	0.155	<u>64.583</u>	<u>59.773</u>	0.919	1.297	0.173	0.248
DMSFE	2.815	0.271	45.833	38.509	-1.015	-1.246	-0.192	-0.238
HR	2.883	0.282	41.667	31.993	-1.597	-1.451	-0.310	-0.280
EHR	2.979	0.322	52.083	41.418	-0.751	-1.080	-0.141	-0.204
EEDF	2.874	0.280	41.667	31.993	-1.597	-1.451	-0.310	-0.280
BMA	2.792	0.223	35.417	35.457	-1.366	-0.756	-0.262	-0.142
FMA-aic	2.785	0.265	<u>60.417</u>	51.790	0.176	-0.787	0.033	-0.147
FMA-bic	2.804	0.269	<u>58.333</u>	50.445	0.055	-0.950	0.010	-0.179
FMA-hq	2.792	0.267	<u>60.417</u>	51.790	0.176	-0.787	0.033	-0.147
RW	2.597	0.193	39.583	37.279				
CT					1.203	1.203	0.229	0.229

See Table 1 for the abbreviation of the models. Underlined **bold** figures indicate that the null hypothesis that the model does not outperform the benchmark model is rejected at the 5% significance level and underlined *italic* figures indicate that the null hypothesis is rejected at the 10% significance level using the stepM-SPA test. The stepM-SPA test is performed setting the dependence parameter q equal to 0.9 and the number of bootstrap simulations is equal to 5000. Both MAE and MSE loss measures are reported in exchange rate levels.

Table 6: Forecasts of the monetary model for the EUR/CHF exchange rate

Model	MAE	MSE	DA	DV	R ^S	R ^F	SR ^S	SR ^F
1-step								
DVAR(2)	0.460	0.013	68.750	64.870	4.641	6.311	0.202	0.279
BDVAR(2)	0.450	0.012	64.583	62.389	3.898	6.261	0.168	0.277
r-BDVAR(2)	<u>0.455</u>	<u>0.012</u>	62.500	63.501	4.257	9.435	0.184	0.440
mean	0.458	0.013	62.500	62.971	4.105	6.006	0.178	0.265
tmean	0.458	0.013	64.583	63.520	4.262	6.006	0.185	0.265
median	0.458	0.013	64.583	63.520	4.262	5.930	0.185	0.261
OLS	0.596	0.019	52.083	50.615	0.444	3.450	0.019	0.149
PC	0.532	0.014	35.417	35.873	-4.479	10.100	-0.194	0.478
DMSFE	0.458	0.013	62.500	62.971	4.105	6.006	0.178	0.265
HR	0.458	0.013	62.500	62.971	4.105	6.006	0.178	0.265
EHR	0.464	0.013	62.500	64.235	4.486	6.367	0.195	0.282
EEDF	0.458	0.013	62.500	62.971	4.105	6.007	0.178	0.265
BMA	0.453	0.012	62.500	61.310	3.596	5.975	0.155	0.263
FMA-aic	0.462	0.013	66.667	64.795	4.620	6.338	0.201	0.281
FMA-bic	0.459	0.013	66.667	64.795	4.620	6.338	0.201	0.281
FMA-hq	0.461	0.013	66.667	64.795	4.620	6.338	0.201	0.281
RW	0.466	0.012	66.667	66.147				
CT					5.092	5.092	0.222	0.222
6-steps								
DVAR(2)	<u>1.294</u>	0.064	68.750	83.363	5.204	3.464	0.604	0.366
mean	1.458	0.075	47.917	67.096	2.656	-0.505	0.273	-0.050
tmean	1.443	0.074	52.083	71.446	3.282	-0.505	0.344	-0.050
median	1.407	0.071	54.167	72.901	3.486	0.905	0.369	0.090
OLS	2.466	0.212	43.750	52.811	0.192	0.505	0.019	0.050
PC	1.681	0.100	31.250	9.990	-6.127	-3.588	-0.769	-0.381
DMSFE	1.446	0.074	52.083	71.446	3.282	-0.505	0.344	-0.050
HR	1.436	0.073	54.167	72.901	3.486	0.725	0.369	0.072
EHR	1.388	0.067	54.167	72.901	3.486	1.021	0.369	0.102
EEDF	1.428	0.072	58.333	76.551	4.111	0.841	0.447	0.084
BMA	1.354	0.066	62.500	81.122	4.891	1.722	0.556	0.173
FMA-aic	1.453	0.074	50.000	67.479	2.710	-0.267	0.279	-0.026
FMA-bic	1.429	0.072	47.917	67.096	2.656	-0.267	0.273	-0.026
FMA-hq	1.443	0.073	50.000	67.479	2.710	-0.267	0.279	-0.026
RW	1.382	0.070	62.500	82.865				
CT					5.160	5.160	0.597	0.597
12-steps								
DVAR(2)	2.233	<u>0.155</u>	70.833	88.077	5.143	3.643	0.795	0.490
s-DVAR(1)	<u>2.191</u>	<u>0.147</u>	68.750	87.814	5.111	3.638	0.787	0.489
mean	2.561	0.193	54.167	66.945	2.163	-1.722	0.270	-0.212
tmean	2.531	0.189	54.167	66.945	2.163	-1.403	0.270	-0.172
median	2.406	0.174	66.667	84.990	4.707	1.281	0.692	0.156
OLS	6.001	1.110	18.750	11.034	-5.187	-5.156	-0.806	-0.798
PC	2.881	0.255	25.000	7.969	-5.605	-5.035	-0.924	-0.768
DMSFE	2.513	0.187	56.250	70.478	2.665	-1.913	0.339	-0.237
HR	2.462	0.181	64.583	83.261	4.500	-0.608	0.648	-0.073
EHR	2.370	<u>0.167</u>	68.750	87.814	5.111	-0.306	0.787	-0.037
EEDF	2.446	0.179	66.667	84.856	4.733	-0.106	0.698	-0.013
BMA	2.292	<u>0.157</u>	68.750	87.814	5.111	3.638	0.787	0.489
FMA-aic	2.557	0.189	52.083	69.145	2.501	-1.328	0.316	-0.162
FMA-bic	2.496	0.182	54.167	72.677	3.003	-0.455	0.389	-0.055
FMA-hq	2.532	0.186	52.083	69.145	2.501	-1.011	0.316	-0.123
RW	2.384	0.182	68.750	87.814				
CT					5.751	5.751	0.971	0.971

See Table 1 for the abbreviation of the models. Underlined **bold** figures indicate that the null hypothesis that the model does not outperform the benchmark model is rejected at the 5% significance level and underlined *italic* figures indicate that the null hypothesis is rejected at the 10% significance level using the stepM-SPA test. The stepM-SPA test is performed setting the dependence parameter q equal to 0.9 and the number of bootstrap simulations is equal to 5000. Both MAE and MSE loss measures are reported in exchange rate levels.

Table 7: Forecasts of the capital flows model for the EUR/CHF exchange rate

Model	MAE	MSE	DA	DV	R ^S	R ^P	SR ^S	SR ^P
1-step								
r-VAR(3)	0.471	0.012	54.167	61.748	3.799	8.308	0.164	0.379
BDVAR(2)	0.457	0.012	66.667	61.846	3.747	7.424	0.162	0.334
r-BDVAR(2)	0.457	0.012	56.250	58.155	2.698	10.476	0.116	0.500
mean	0.480	0.012	54.167	49.859	0.140	10.023	0.006	0.473
tmean	0.479	0.012	56.250	53.535	1.275	10.023	0.054	0.473
median	0.477	0.012	56.250	53.535	1.275	10.317	0.054	0.491
OLS	0.641	0.019	52.083	56.286	1.905	2.586	0.081	0.111
PC	0.525	0.013	33.333	32.405	-5.457	9.209	-0.239	0.427
DMSFE	0.478	0.012	56.250	53.535	1.275	10.023	0.054	0.473
HR	0.478	0.012	54.167	49.859	0.140	10.023	0.006	0.473
EHR	0.470	0.012	58.333	62.853	4.114	10.747	0.178	0.517
EEDF	0.478	0.012	54.167	53.417	1.242	10.023	0.053	0.473
BMA	0.455	0.012	60.417	62.906	4.129	9.429	0.179	0.440
FMA-aic	0.487	0.012	58.333	49.158	-0.164	10.023	-0.007	0.473
FMA-bic	0.482	0.012	58.333	49.484	0.013	10.023	0.001	0.473
FMA-hq	0.485	0.012	60.417	53.900	1.379	10.023	0.059	0.473
RW	0.466	0.012	66.667	66.147				
CT					5.092	5.092	0.222	0.222
6-steps								
r-VAR(3)	1.327	0.064	62.500	77.336	4.346	2.774	0.478	0.286
r-BDVAR(2)	1.363	0.065	62.500	82.865	5.160	1.606	0.597	0.161
mean	1.573	0.086	29.167	27.782	-3.273	-1.660	-0.343	-0.167
tmean	1.539	0.083	31.250	32.202	-2.542	-1.682	-0.260	-0.169
median	1.419	0.072	56.250	66.557	2.827	0.695	0.292	0.069
OLS	2.307	0.175	45.833	37.999	-2.181	-2.529	-0.221	-0.259
PC	1.700	0.104	29.167	7.555	-6.467	-5.106	-0.841	-0.589
DMSFE	1.525	0.081	35.417	35.169	-2.120	-1.780	-0.215	-0.179
HR	1.540	0.082	31.250	29.069	-3.093	-1.494	-0.322	-0.150
EHR	1.437	0.071	50.000	65.360	2.228	-0.210	0.227	-0.021
EEDF	1.521	0.080	31.250	29.069	-3.093	-1.048	-0.322	-0.104
BMA	1.366	0.066	60.417	74.215	3.820	0.774	0.410	0.077
FMA-aic	1.612	0.090	25.000	11.947	-5.796	-2.899	-0.705	-0.300
FMA-bic	1.551	0.084	39.583	39.859	-1.275	-0.797	-0.127	-0.079
FMA-hq	1.587	0.087	29.167	18.606	-4.683	-1.181	-0.525	-0.118
RW	1.382	0.070	62.500	82.865				
CT					5.160	5.160	0.597	0.597
12-steps								
r-DVAR(3)	2.323	<u>0.155</u>	68.750	87.814	5.111	2.715	0.787	0.347
BDVAR(2)	2.317	<u>0.161</u>	68.750	87.814	5.111	2.921	0.787	0.377
mean	2.741	0.226	22.917	10.808	-5.118	-4.783	-0.789	-0.709
tmean	2.681	0.215	31.250	24.470	-3.304	-4.260	-0.435	-0.600
median	2.416	0.173	64.583	82.427	4.432	2.134	0.634	0.266
OLS	5.351	0.910	35.417	34.090	-1.879	-1.971	-0.233	-0.245
PC	3.002	0.281	20.833	6.252	-5.811	-5.782	-0.991	-0.981
DMSFE	2.699	0.218	25.000	12.781	-4.897	-3.444	-0.735	-0.457
HR	2.702	0.219	25.000	12.200	-4.945	-4.715	-0.746	-0.694
EHR	2.520	0.189	47.917	53.775	0.320	-1.914	0.039	-0.237
EEDF	2.668	0.213	27.083	18.321	-4.168	-3.903	-0.583	-0.535
BMA	2.345	<u>0.157</u>	68.750	87.814	5.111	2.616	0.787	0.332
FMA-aic	2.763	0.233	25.000	11.871	-4.934	-4.534	-0.744	-0.655
FMA-bic	2.654	0.214	37.500	33.806	-1.900	-4.109	-0.235	-0.572
FMA-hq	2.717	0.225	33.333	24.588	-3.163	-4.109	-0.413	-0.572
RW	2.384	0.182	68.750	87.814				
CT					5.751	5.751	0.971	0.971

See Table 1 for the abbreviation of the models. Underlined **bold** figures indicate that the null hypothesis that the model does not outperform the benchmark model is rejected at the 5% significance level and underlined *italic* figures indicate that the null hypothesis is rejected at the 10% significance level using the stepM-SPA test. The stepM-SPA test is performed setting the dependence parameter q equal to 0.9 and the number of bootstrap simulations is equal to 5000. Both MAE and MSE loss measures are reported in exchange rate levels.

Table 8: Forecasts of the monetary model for the EUR/JPY exchange rate

Model	MAE	MSE	DA	DV	R ^S	R ^F	SR ^S	SR ^F
1-step								
r-VAR(5)	9.597	3.161	64.583	66.450	10.477	14.344	0.281	0.398
r-VEC(1,4)	9.698	3.061	75.000	81.341	19.435	17.479	0.580	0.506
s-DVAR(1)	10.109	3.224	<i>70.833</i>	<i>73.905</i>	14.525	18.467	0.404	0.542
mean	9.808	3.104	66.667	<i>72.291</i>	13.523	15.361	0.372	0.432
tmean	9.790	3.083	68.750	<i>72.358</i>	13.561	15.361	0.373	0.432
median	9.855	3.105	66.667	<i>72.255</i>	13.488	15.361	0.371	0.432
OLS	11.614	4.867	64.583	63.584	8.092	12.737	0.213	0.348
PC	10.147	3.430	60.417	60.821	6.169	15.491	0.161	0.436
DMSFE	9.816	3.109	64.583	<i>72.189</i>	13.450	15.361	0.370	0.432
HR	9.808	3.109	64.583	<i>72.189</i>	13.450	15.361	0.370	0.432
EHR	10.001	3.222	64.583	<i>71.536</i>	12.945	17.479	0.354	0.506
EEDF	9.808	3.108	66.667	<i>72.291</i>	13.523	15.361	0.372	0.432
BMA	10.581	3.742	62.500	<u>61.932</u>	7.572	15.810	0.199	0.447
FMA-aic	9.874	3.175	64.583	69.715	11.857	15.361	0.321	0.432
FMA-bic	9.879	3.162	66.667	<i>71.638</i>	13.018	15.361	0.356	0.432
FMA-hq	9.875	3.169	66.667	<i>71.638</i>	13.018	15.361	0.356	0.432
RW	10.846	3.787	50.000	47.377				
MA(1,2)					13.113	13.113	0.359	0.359
6-steps								
VEC(3,4)	32.600	37.962	70.833	74.967	8.818	7.481	0.460	0.379
r-VEC(1,4)	33.636	37.206	66.667	74.364	8.294	5.953	0.427	0.294
s-DVAR(1)	34.281	39.920	60.417	63.397	4.859	8.586	0.236	0.445
mean	33.398	37.417	66.667	72.112	7.601	5.878	0.386	0.290
tmean	33.303	37.218	62.500	70.286	7.013	5.878	0.352	0.290
median	33.438	38.168	60.417	73.208	8.148	8.586	0.418	0.445
OLS	68.709	183.974	33.333	45.166	-1.959	-0.745	-0.093	-0.035
PC	45.050	54.003	37.500	44.744	-2.015	-1.073	-0.096	-0.051
DMSFE	33.805	38.557	60.417	67.539	6.171	5.878	0.305	0.290
HR	33.626	37.830	60.417	69.656	6.806	5.878	0.340	0.290
EHR	36.081	42.826	50.000	51.335	0.376	2.690	0.018	0.128
EEDF	33.730	38.141	58.333	66.910	5.965	5.878	0.294	0.290
BMA	37.417	52.186	62.500	51.877	1.362	6.757	0.065	0.338
FMA-aic	33.400	38.273	68.750	72.913	8.040	6.578	0.412	0.328
FMA-bic	33.405	38.068	60.417	69.560	6.870	6.645	0.344	0.331
FMA-hq	33.400	38.157	62.500	72.307	7.712	6.645	0.392	0.331
RW	35.175	40.292	54.167	49.758				
CT					11.033	11.033	0.614	0.614
12-steps								
r-DVAR(4)	50.300	82.269	62.500	58.000	2.160	4.657	0.141	0.315
r-VEC(1,4)	52.361	78.072	68.750	79.927	7.695	0.645	0.573	0.042
mean	55.109	82.390	50.000	66.354	4.311	0.817	0.290	0.053
tmean	54.224	81.031	56.250	70.127	5.335	1.042	0.367	0.067
median	52.994	81.454	58.333	66.689	4.454	4.263	0.300	0.286
OLS	259.613	15520.07	52.083	57.634	1.732	1.212	0.112	0.078
PC	68.798	108.895	39.583	49.494	-0.143	-0.143	-0.009	-0.009
DMSFE	55.752	87.052	45.833	54.115	1.151	0.681	0.074	0.044
HR	55.602	86.815	50.000	61.268	2.956	0.681	0.194	0.044
EHR	58.006	103.438	45.833	42.785	-1.909	3.068	-0.124	0.202
EEDF	54.692	85.505	56.250	63.385	3.453	2.678	0.228	0.175
BMA	53.266	89.276	54.167	49.705	0.084	1.661	0.005	0.108
FMA-aic	59.060	104.188	50.000	65.600	4.296	2.033	0.288	0.132
FMA-bic	58.271	103.610	60.417	71.336	5.698	2.033	0.396	0.132
FMA-hq	58.738	103.905	54.167	71.524	5.802	2.033	0.404	0.132
RW	53.562	84.720	60.417	50.506				
CT					0.143	0.143	0.009	0.009

See Table 1 for the abbreviation of the models. Underlined **bold** figures indicate that the null hypothesis that the model does not outperform the benchmark model is rejected at the 5% significance level and underlined *italic* figures indicate that the null hypothesis is rejected at the 10% significance level using the stepM-SPA test. The stepM-SPA test is performed setting the dependence parameter q equal to 0.9 and the number of bootstrap simulations is equal to 5000. Both MAE and MSE loss measures are reported in exchange rate levels (multiplied by 1000).

Table 9: Forecasts of the capital flows model for the EUR/JPY exchange rate

Model	MAE	MSE	DA	DV	R^S	R^F	SR^S	SR^F
1-step								
s-VAR(2)	10.396	3.761	62.500	65.568	9.070	11.336	0.240	0.306
rs-VAR(2)	10.115	3.450	60.417	62.687	8.001	15.885	0.211	0.449
rs-DVAR(1)	10.432	3.471	60.417	67.005	10.238	18.394	0.274	0.540
r-BDVAR(4)	10.586	3.487	58.333	67.244	10.043	16.277	0.268	0.463
mean	10.458	3.489	56.250	59.546	5.476	15.854	0.143	0.448
tmean	10.461	3.479	54.167	58.804	5.027	15.651	0.131	0.441
median	10.365	3.415	52.083	58.524	4.860	15.854	0.126	0.448
OLS	12.761	5.955	52.083	55.323	2.361	9.797	0.061	0.261
PC	10.804	3.855	56.250	57.820	4.608	11.002	0.120	0.296
DMSFE	10.468	3.490	54.167	58.804	5.027	15.651	0.131	0.441
HR	10.458	3.507	58.333	59.885	5.678	15.854	0.148	0.448
EHR	10.644	3.757	60.417	59.591	5.731	11.587	0.149	0.313
EEDF	10.458	3.501	58.333	59.885	5.678	15.854	0.148	0.448
BMA	11.115	3.905	56.250	56.768	4.204	11.587	0.109	0.313
FMA-aic	10.784	3.702	56.250	55.711	3.606	11.587	0.093	0.313
FMA-bic	10.634	3.624	58.333	58.543	5.154	11.587	0.134	0.313
FMA-hq	10.729	3.672	56.25	55.711	3.606	11.587	0.093	0.313
RW	10.846	3.787	50.000	47.377				
MA(1,2)					13.113	13.113	0.359	0.359
6-steps								
VEC(3,5)	41.446	47.998	47.917	60.077	3.716	3.492	0.179	0.168
r-VAR(5)	35.120	37.357	52.083	58.844	3.005	5.903	0.144	0.291
rs-DVAR(1)	34.342	39.793	56.250	52.557	1.059	6.662	0.050	0.332
BDVAR(4)	35.005	41.045	52.083	51.118	0.491	6.886	0.023	0.345
r-BDVAR(4)	34.635	40.101	58.333	55.523	2.126	4.697	0.101	0.228
mean	34.735	38.983	47.917	55.271	1.929	5.717	0.092	0.281
tmean	34.628	39.041	50.000	58.842	3.191	5.518	0.153	0.271
median	34.558	39.063	50.000	58.861	3.232	6.020	0.155	0.297
OLS	89.749	245.415	29.167	29.969	-7.072	-8.722	-0.355	-0.454
PC	46.668	56.433	35.417	43.706	-2.402	-1.333	-0.114	-0.063
DMSFE	34.656	39.641	52.083	57.601	2.658	5.953	0.127	0.294
HR	34.650	39.133	50.000	58.842	3.191	5.704	0.153	0.280
EHR	36.538	43.231	50.000	45.175	-1.505	3.908	-0.071	0.188
EEDF	34.545	39.214	52.083	60.527	3.735	6.020	0.180	0.297
BMA	37.851	45.268	54.167	57.833	2.779	7.057	0.133	0.355
FMA-aic	37.417	42.311	43.750	54.033	1.820	5.717	0.086	0.281
FMA-bic	36.128	41.306	50.000	58.796	3.352	5.903	0.161	0.291
FMA-hq	36.940	41.923	47.917	58.211	3.157	5.717	0.151	0.281
RW	35.175	40.292	54.167	49.758				
CT					11.033	11.033	0.614	0.614
12-steps								
VEC(3,5)	62.027	98.162	60.417	73.658	6.351	4.028	0.450	0.269
r-VAR(5)	52.307	70.151	56.250	69.804	5.362	5.314	0.369	0.365
r-DVAR(4)	51.909	85.596	66.667	59.858	2.536	2.773	0.166	0.182
mean	55.06	81.315	50.000	63.847	3.813	2.676	0.254	0.175
tmean	54.593	80.864	54.167	69.164	5.142	2.676	0.352	0.175
median	53.457	81.261	58.333	63.738	3.773	2.838	0.251	0.186
OLS	108.833	508.058	72.917	67.095	4.442	4.442	0.299	0.299
PC	67.624	106.270	39.583	49.494	-0.143	-1.186	-0.009	-0.077
DMSFE	56.015	86.770	43.750	51.634	0.706	1.988	0.046	0.129
HR	55.443	84.077	50.000	57.991	2.314	1.944	0.151	0.126
EHR	56.904	95.476	47.917	37.993	-3.104	0.487	-0.204	0.031
EEDF	55.146	84.101	52.083	61.433	3.172	1.988	0.209	0.129
BMA	61.779	106.788	50.000	49.575	0.172	-0.074	0.011	-0.005
FMA-aic	56.203	86.559	56.250	63.020	3.700	3.385	0.246	0.224
FMA-bic	55.260	85.458	62.500	68.088	4.873	3.128	0.331	0.206
FMA-hq	55.803	86.125	56.250	63.020	3.700	3.385	0.246	0.224
RW	53.562	84.720	60.417	50.506				
CT					0.143	0.143	0.009	0.009

See Table 1 for the abbreviation of the models. Underlined **bold** figures indicate that the null hypothesis that the model does not outperform the benchmark model is rejected at the 5% significance level and underlined *italic* figures indicate that the null hypothesis is rejected at the 10% significance level using the stepM-SPA test. The stepM-SPA test is performed setting the dependence parameter q equal to 0.9 and the number of bootstrap simulations is equal to 5000. Both MAE and MSE loss measures are reported in exchange rate levels (multiplied by 1000).